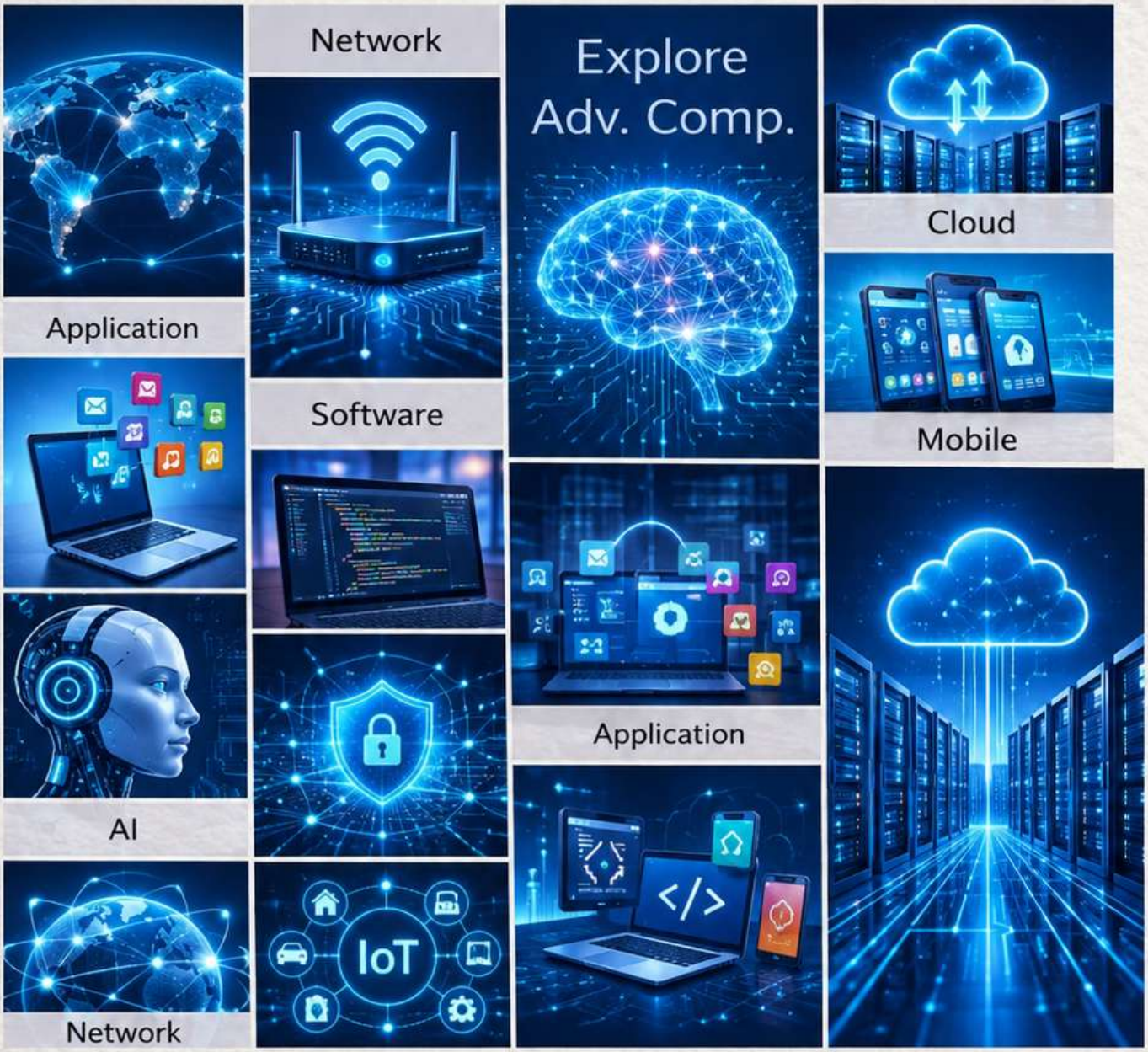
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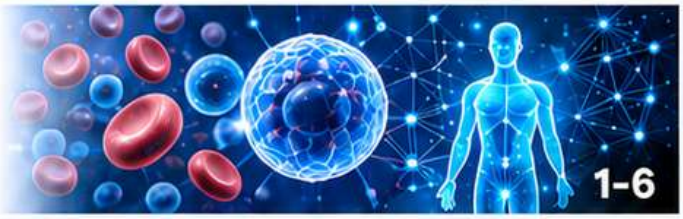
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Artificial Intelligence for Blood Cancer Detection: Literature Benchmarks and Healthcare Professional Perceptions

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Abstract—Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has shown strong research performance in the analysis of blood smears and other hematology data. However, high benchmark accuracy does not by itself establish clinical effectiveness. This study combines a review of AI approaches for blood cancer detection with a cross-sectional survey of 32 healthcare professionals to examine perceived diagnostic value, trust, and implementation barriers. Participants included doctors (40%), nurses (35%), and laboratory technicians (25%). Respondents rated AI-supported diagnostic speed and continuous monitoring relatively favorably (M=3.8, SD=1.0 for each), and future dependence on AI diagnosis received M=3.6 (SD=1.2). Participants with prior experience of AI medical tools expressed more favorable views than those without such experience, $t(30)=4.92$, $p<0.001$. Perceptions did not differ significantly across professional groups, $F(2,29)=1.84$, $p>0.05$. Perceived AI use correlated with perceived diagnostic precision ($r=0.67$), while perceived decision support correlated with trust ($r=0.61$). Model-performance figures in the source report are derived from published studies and public benchmark datasets rather than a locally validated clinical model; they are therefore treated as secondary evidence. The paper synthesizes verified leukemia-imaging literature, discusses dataset shift, patient-level validation, calibration, explainability, fairness, and clinical workflow integration, and proposes a rigorous validation framework for future AI-assisted hematology research in Oman. AI is positioned as decision support rather than a replacement for clinical expertise.

Keywords—artificial intelligence; leukemia; blood cancer; deep learning; convolutional neural networks; blood smear; clinical decision support; hematology; Oman

I. INTRODUCTION

Hematologic malignancies include leukemias, lymphomas, and related disorders that affect blood, bone marrow, and lymphatic tissues. Their diagnosis can involve complete blood counts, peripheral-blood-smear examination, bone-marrow assessment, immunophenotyping, cytogenetics, molecular tests, and expert clinical interpretation. Microscopy remains important because abnormal cell morphology can provide rapid diagnostic clues, yet manual examination is labor-intensive and depends on specialist expertise.

AI has become increasingly prominent in hematology because image classification, segmentation, prediction, and risk-stratification tasks can be formulated using ML or DL. A comprehensive review of 144 studies published between 2015 and 2021 found substantial activity in AI applications across hematologic malignancy screening, diagnosis, and treatment, while also identifying unresolved gaps in translation across the patient pathway [1]. Deep neural networks are especially relevant to blood-smear imaging because convolutional architectures can learn complex morphological patterns directly from labeled images.

Nevertheless, research accuracy and clinical utility are not equivalent. A model trained on a curated public dataset may perform well under a particular imaging protocol but degrade when applied to images from another microscope, staining procedure, hospital, or patient population. Clinical deployment therefore requires more than a high accuracy value: sensitivity, specificity, calibration, error analysis, external validation, workflow fit, transparency, privacy, and clinician oversight all matter.

The present study combines two evidence streams. First, it reviews literature and public benchmark evidence on AI-assisted blood cancer detection. Second, it analyzes perceptions from 32 healthcare professionals regarding AI speed, monitoring, decision support, trust, and implementation. Importantly, the model-performance numbers reported in the source document are not treated as results of a newly trained local model because the report itself states that model performance was based on published literature and publicly accessible blood-smear datasets.

A. Objectives and Research Questions

The paper aims to assess the potential contribution of AI to blood cancer detection, compare major ML/DL approaches reported in the literature, analyze healthcare-professional perceptions, identify clinical and ethical barriers, and define a validation pathway suitable for future work in Oman. The central question is not simply whether AI can classify images accurately, but under what conditions such performance can be translated into safe clinical decision support.

II. CLINICAL AND TECHNICAL BACKGROUND

A. AI in Hematology

The hematology literature includes classical ML methods using engineered laboratory or morphological features and DL methods that learn representations directly from images or high-dimensional data. El Alaoui et al. identified ML, leukemia, classification, and DL as prominent themes in AI hematology research and concluded that the field has produced impressive results while leaving important clinical-pathway questions unresolved [1]. This supports a balanced interpretation: AI is technically promising, but evidence quality and clinical generalizability vary across studies.

B. Blood-Smear Image Classification

Public image datasets have accelerated leukemia research by providing labeled examples for segmentation and classification. ALL-IDB was introduced as an image database for acute lymphoblastic leukemia (ALL) image-processing research [2]. More recent datasets and challenge collections have enabled larger-scale comparisons, but many remain curated and relatively homogeneous. Benchmark success therefore provides evidence of algorithmic capability rather than a guarantee of performance in routine hospital practice.

Deep CNNs learn hierarchical features such as edges, textures, nuclei morphology, and cell-level structure without requiring every feature to be manually engineered. Transfer learning can reduce training requirements by adapting networks pretrained on large image collections. Ensemble methods can combine complementary models and sometimes produce strong benchmark performance. A 2024 study by

Awais et al., for example, evaluated deep features and ensemble methods for ALL classification on public data, illustrating the high performance achievable under benchmark conditions [3]. Such results are valuable, but must be interpreted within the dataset and evaluation protocol used.

C. Evaluation Beyond Accuracy

Accuracy can be misleading when class prevalence is unequal or when false negatives and false positives have different clinical costs. A leukemia screening system should therefore report sensitivity (recall for disease), specificity, precision, F1-score, receiver-operating-characteristic area under the curve (AUROC), and preferably precision-recall metrics for imbalanced settings. Calibration is also important: if a model reports a 90% probability, cases with similar scores should be correct at approximately that rate. Without calibration, confidence values may appear precise while being clinically unreliable.

D. Clinical Translation, Ethics, and Governance

WHO guidance emphasizes that AI for health should place ethics, human rights, transparency, accountability, inclusiveness, and safety at the center of design and deployment [4]. In blood cancer diagnostics, these principles translate into requirements for representative datasets, secure handling of sensitive data, documented model limitations, human oversight, and mechanisms for monitoring performance after deployment. A clinically responsible model should support—not replace—the hematologist, pathologist, or laboratory specialist.

E. Research Gap

Much of the leukemia-AI literature demonstrates technical feasibility on retrospective or public datasets, while comparatively fewer studies address prospective clinical validation, domain shift, local workflow integration, and health-professional trust. The current paper addresses this gap by combining secondary technical evidence with primary perception data and by separating algorithmic benchmark performance from clinically validated effectiveness.

III. METHODOLOGY

The study uses a mixed evidence-assessment design comprising a review/secondary analysis of AI model performance reported in published literature and public blood-smear resources, together with a cross-sectional questionnaire of healthcare professionals. This wording more accurately reflects the available evidence than describing the study as a full local clinical model-development experiment.

A. Healthcare-Professional Survey

Thirty-two healthcare professionals completed a 13-item Likert-scale questionnaire. Doctors represented 40% of the sample, nurses 35%, and laboratory technicians 25%. Items covered perceived effects of AI on diagnostic speed, continuous monitoring, decision support, future dependence, workload, treatment timing, trust, and related concerns. Google Forms was used for collection, and responses were exported for descriptive and inferential analysis.

B. Secondary Technical Evidence

The source report refers to hundreds of blood-smear images from open repositories and to model classes including CNN and SVM. However, it later clarifies that AI/ML performance evaluation was based on verified results from published literature and publicly accessible datasets because locally annotated medical image data were limited. Consequently, this publication-ready version does not present 95% or 97% model accuracy as an original locally trained result. Instead, literature benchmark results are discussed explicitly as secondary evidence.

C. Statistical Analysis

Descriptive statistics summarize professional perceptions. An independent-samples t-test compared respondents with and without prior experience of AI medical tools. One-way ANOVA compared perceptions across doctors, nurses, and laboratory technicians. Pearson correlations examined associations between perceived AI use and perceived diagnostic precision, and between perceived decision support and trust. These tests concern participant perceptions; they do not measure the diagnostic accuracy of an AI model on patients.

D. Ethical Considerations

The questionnaire was voluntary and anonymous. Publicly available medical datasets were described as anonymized. No conclusion from the study should be used as individual medical advice or as authorization for autonomous diagnosis. Future clinical studies require ethics approval, appropriate data-governance agreements, patient-level privacy safeguards, and careful consideration of whether data reuse is compatible with original consent and local regulation.

IV. RESULTS

A. Descriptive Professional Perceptions

Healthcare professionals reported moderately favorable views of several AI functions. The statement that AI speeds diagnosis had a mean of 3.8 (SD=1.0), and continuous observation/monitoring also had a mean of 3.8 (SD=1.0). Future dependence on AI diagnosis received a mean of 3.6 (SD=1.2). The item stating that AI shortens the time needed for therapy received a lower mean of 3.1 (SD=1.3), suggesting that respondents distinguished diagnostic support from downstream treatment effects.

B. Inferential Perception Analysis

Participants with prior experience using AI medical tools expressed significantly more favorable perceptions of AI effectiveness than those without such experience, $t(30)=4.92$, $p<0.001$. By contrast, professional role was not associated with a statistically significant difference in perceptions, $F(2,29)=1.84$, $p>0.05$. These results indicate that familiarity may be more relevant to acceptance than profession within this small sample, although group sizes and effect sizes should be reported in future work for fuller interpretation.

Perceived AI application was positively correlated with perceived diagnostic precision ($r=0.67$), while perceived AI decision support was positively correlated with trust ($r=0.61$). These are substantial sample correlations, but they measure relationships among perceptions. They do not show that increasing AI utilization causes actual diagnostic accuracy to increase.

C. Technical Benchmark Evidence

The source report summarizes deep-learning results from the literature and gives illustrative values such as approximately 95% for CNN-based approaches and up to 97% for hybrid DL approaches. Because these values were drawn

from secondary sources rather than a documented local experiment, they should not be combined into a single "study accuracy." Verified published studies demonstrate that benchmark accuracy can indeed be high. For example, Awais et al. reported strong ALL classification results using public datasets and deep feature/ensemble techniques [3]. The correct interpretation is that AI has demonstrated technical feasibility under defined research conditions, while local clinical performance remains unknown.

D. Key Result Distinction

V. DISCUSSION

A. Diagnostic Potential and the Benchmark-to-Clinic Gap

The literature strongly supports the ability of DL systems to discriminate leukemia-related image patterns under research conditions [1], [3]. However, the benchmark-to-clinic gap is central. Model performance may change with staining, image magnification, scanner characteristics, laboratory preparation, patient demographics, disease subtype, or prevalence. External validation should therefore use data collected independently from the training source and should preserve patient-level separation so that images from the same patient cannot appear in both training and test sets.

B. Sensitivity, Specificity, and Clinical Cost

For early screening, false negatives can delay further investigation, while false positives can create unnecessary anxiety and testing. Model selection should therefore consider clinically meaningful trade-offs rather than maximizing overall accuracy alone. Thresholds may need to be selected according to intended use: a screening aid may prioritize sensitivity, while a confirmatory support system may require stronger specificity. Decision-curve analysis or cost-sensitive evaluation can complement conventional metrics when the clinical action associated with each prediction is defined.

C. Trust, Experience, and Human Oversight

The t-test and correlation results indicate that prior AI experience and perceived decision support are associated with more favorable attitudes and trust. This is plausible because familiarity can reduce uncertainty about how a tool works. Yet trust should be calibrated rather than maximized. Over-trust can lead clinicians to accept incorrect outputs, while under-trust can prevent beneficial tools from being used. Interfaces should therefore expose confidence, uncertainty, and the evidence available for review, and should make it easy for professionals to disagree with the model.

D. Explainability and Error Analysis

In image-based hematology, explainability can include saliency or attention maps that identify regions influencing a prediction, but visual explanations should not be assumed to be clinically meaningful without validation. More useful error analysis may categorize false predictions by cell quality, staining artifact, subtype, low blast count, or ambiguous morphology. Clinician review of error clusters can reveal whether a model is learning medically relevant patterns or relying on spurious visual cues.

E. Data Quality, Bias, and Generalizability

The review literature repeatedly identifies dataset size and quality as constraints. A dataset can be large yet still biased if images originate from a small number of patients or a single laboratory. Generalizable evaluation requires diversity in patient demographics, acquisition equipment, clinical sites, and disease presentation. Sampling should occur at the patient level, and the test set should reflect realistic prevalence or be accompanied by prevalence-adjusted predictive values.

F. Implications for Oman

For Oman, a realistic first step is not immediate autonomous deployment but a carefully governed validation program. A national or multi-hospital collaboration could create an anonymized, quality-controlled hematology dataset representing local laboratory workflows. Models could then be externally tested against expert review, with performance reported separately by hospital, equipment type, and clinically relevant subgroup. This approach would generate evidence that is more useful for local adoption than importing an accuracy number from an unrelated benchmark.

VI. PROPOSED CLINICAL VALIDATION FRAMEWORK

A. Dataset Curation and Splitting

Future model-development work should define inclusion criteria, diagnostic reference standards, and image-quality requirements before training begins. Patient-level identifiers should be used solely to enforce train/validation/test separation and then protected or removed according to governance requirements. Data augmentation may increase visual diversity, but synthetic variation must not be treated as a substitute for independent clinical data.

B. Model Development and Baselines

A strong study should compare advanced deep networks with transparent baselines. Classical ML on engineered morphology or laboratory features, a standard transfer-learning CNN, and a more complex ensemble can be evaluated under the same split. Reporting only the best model creates selection bias; all prespecified baselines and tuning procedures should be documented. Hyperparameter optimization must be confined to training/validation data to preserve the integrity of the final test set.

C. Performance and Calibration

The minimum reporting set should include sensitivity, specificity, precision, negative predictive value, F1-score, AUROC, confusion matrices, and confidence intervals. When probabilistic outputs are used, calibration curves and a metric such as Brier score should be included. Results should be presented at the patient level whenever clinical decisions are patient-based. If multiple images are obtained from one patient, image-level accuracy can otherwise give an inflated impression of independence.

D. External and Prospective Validation

After internal testing, the model should be evaluated on a fully independent hospital or time period. Prospective silent deployment is a useful intermediate stage: the system generates predictions without influencing care, allowing researchers to compare outputs with routine diagnosis and identify workflow or distribution problems. Only after adequate prospective evidence should an interventional study evaluate whether the tool changes diagnostic time, error rates, workload, or patient management.

E. Human Factors and Governance

Clinical validation should include healthcare professionals because technical performance alone does not determine adoption. Usability, alarm fatigue, explanation quality, confidence calibration, workflow integration, and responsibility for errors should be tested. WHO guidance

provides an appropriate governance foundation emphasizing safety, transparency, accountability, inclusiveness, and protection of human autonomy [4].

F. Reference Standard and Label Quality

A medical AI model can only be as reliable as its reference labels. For leukemia research, labels may be derived from expert morphology, immunophenotyping, bone-marrow findings, molecular testing, or a combination of evidence. Image labels created solely from one reader's visual judgment can contain uncertainty, especially in borderline cases. Future datasets should document how diagnoses were established, whether multiple experts reviewed difficult cases, and how disagreements were resolved. When label uncertainty is clinically meaningful, forcing every case into a single hard class may hide important ambiguity.

The reference standard should also match the intended task. A system designed to flag abnormal cells for review is different from a system claiming to diagnose a leukemia subtype. The former may use cell-level annotation and prioritize high sensitivity, whereas the latter requires patient-level diagnostic evidence and a much more demanding validation pathway. Precise definition of intended use prevents performance claims from exceeding what the data can support.

G. Domain Shift and Laboratory Variation

Blood-smear images can vary because of staining protocols, illumination, microscope optics, camera sensors, image compression, slide preparation, and technician practice. A network may inadvertently learn site-specific visual characteristics rather than general disease morphology. This phenomenon, often described as domain shift, is one reason that random image-level train/test splits can overestimate performance if images from the same patient or laboratory appear in both sets.

Robust evaluation should therefore include site-held-out or time-held-out testing. If multiple hospitals participate, one hospital can be excluded from training and used as an external test site. Performance drops should be reported rather than hidden through additional tuning on the test data. Domain-adaptation methods can later be investigated, but they should be evaluated against a clearly defined external baseline.

H. Class Imbalance and Clinically Relevant Prevalence

Many research datasets intentionally balance normal and abnormal images to simplify model development. Balanced datasets are useful for comparing algorithms, but they do not necessarily reflect clinical prevalence. Predictive values depend on prevalence, so a model that performs impressively on a balanced benchmark may generate a different proportion of false alerts in routine screening. Future studies should therefore report both balanced benchmark metrics and performance under a prevalence distribution that resembles the intended use environment.

Where rare subtypes are included, macro-averaged metrics can prevent common classes from dominating the result. Confusion matrices should be presented at both cell and patient levels where applicable. Rare but clinically important errors deserve qualitative review even if they have little effect on aggregate accuracy.

I. Explainability as a Clinical Evaluation Question

Explainability should be evaluated with clinicians rather than treated as a decorative visualization. A heatmap that highlights the correct cell region may increase confidence, but it does not necessarily explain which morphological features drove the classification. Conversely, a textual explanation generated by a language model may sound plausible without being faithful to the underlying classifier. Future work should test whether explanations help professionals detect model errors, understand uncertainty, or make better decisions compared with predictions alone.

Useful explanation formats may differ by role. Laboratory specialists may prefer cell-level morphology cues and segmentation overlays, whereas physicians may need patient-level summaries that integrate laboratory findings with uncertainty. The survey sample includes doctors, nurses, and laboratory technicians; future questionnaires could therefore examine role-specific explanation needs rather than asking about general trust in AI.

J. Post-Deployment Monitoring

Clinical AI validation does not end at deployment. Changes in laboratory equipment, staining procedures, patient populations, or clinical workflows can alter the data distribution over time. A deployed system should therefore be monitored for changes in sensitivity, specificity, calibration, and usage patterns. Performance thresholds and escalation procedures should be agreed before clinical use so that the system can be paused or reviewed if drift is detected.

Audit logs should capture model version, input provenance, output, confidence, and clinician action without unnecessarily exposing patient information. Monitoring should also identify whether clinicians consistently override the model in particular scenarios. Repeated disagreement may signal a model limitation, a workflow problem, or a training need and should trigger structured review.

K. Reproducibility and Reporting Standards

Future technical studies should provide enough information for independent replication: dataset source and version, number of patients and images, inclusion/exclusion criteria, split method, preprocessing, augmentation, architecture, initialization, optimizer, learning-rate schedule, stopping rule, hyperparameter selection, and software environment. The source report currently aggregates figures from several studies; reproducible local research will require a single clearly documented pipeline.

Confidence intervals should accompany performance metrics. If models are compared, statistical comparisons should respect paired predictions on the same test cases. Repeated cross-validation can be useful during development, but a final untouched external test set remains essential. Reporting should also state whether model selection was based on accuracy, sensitivity, AUROC, or another prespecified criterion to reduce selective reporting.

L. Proposed Oman Pilot Study

A feasible Oman pilot could begin with retrospective blood-smear images from one institution and an external validation set from a second institution, subject to ethics and data-sharing approvals. Expert hematology or pathology review would define the reference standard. The first model could focus on a narrow triage task—such as distinguishing clearly normal from suspicious smears—rather than attempting autonomous

leukemia diagnosis. Narrow intended use makes error analysis and safety evaluation more tractable.

After retrospective validation, a silent prospective phase could process incoming images without displaying predictions to clinicians. Researchers could compare the model output with routine diagnosis, measure processing latency, and identify cases that fall outside the training distribution. If performance remains acceptable, a later decision-support study could show predictions to clinicians and measure whether the tool changes review time, sensitivity, workload, or disagreement rates. This staged approach produces stronger clinical evidence than moving directly from public benchmark accuracy to deployment.

M. Health-Professional Training and Adoption

The professional survey suggests that familiarity with AI is associated with more favorable perceptions. Training may therefore influence adoption, but education should include limitations as well as capabilities. Clinicians need to understand that a model can be highly accurate overall yet fail systematically on an underrepresented subgroup or unfamiliar acquisition condition. Training should cover confidence interpretation, appropriate override behavior, reporting of suspected errors, and the distinction between decision support and final clinical responsibility.

Trust can be strengthened through transparency about validation and monitoring rather than through promotional claims. Providing clinicians with local validation results, examples of known failure modes, and clear escalation pathways may produce more appropriately calibrated trust than presenting only headline accuracy.

N. Proposed Experimental Reporting Template

A future Oman-based technical paper should report its dataset in a way that separates patients, slides, and image patches. The number of images alone is insufficient because hundreds of patches can originate from a small number of patients. A dataset table should therefore state the number of patients in each class, number of slides, number of extracted cells or patches, acquisition site, staining procedure, imaging device, and reference-standard procedure. Train, validation, and test partitions should be defined at patient level and frozen before final evaluation.

For each model, the paper should report architecture, parameter initialization, input resolution, augmentation, optimizer, batch size, learning rate, number of epochs, early-stopping criteria, and the rule used to select the final checkpoint. If transfer learning is used, the pretrained source and which layers were fine-tuned should be stated. These details are necessary because apparently small implementation choices can produce large differences in medical-image performance and are essential for reproducibility.

O. Patient-Level Versus Cell-Level Decisions

Many leukemia image studies classify individual cells, while clinical decisions are made for patients. A patient may contribute many cell images, and these images are statistically dependent. Future work should define how cell-level predictions are aggregated into a patient-level recommendation. Possible strategies include majority voting, proportion of suspicious cells, attention-based pooling, or rules that incorporate laboratory values. The aggregation method must be evaluated separately because high cell-level accuracy does not automatically translate into reliable patient-level triage.

Patient-level evaluation also changes the interpretation of errors. A single incorrectly classified cell may be clinically unimportant if the overall smear contains many correctly identified abnormal cells, while missing all abnormal cells in one patient is a serious failure. Reporting should therefore include patient-level sensitivity and specificity in addition to image-level metrics.

P. Multi-Modal Opportunities

Blood cancer diagnosis rarely depends on one image source alone. A future system could combine blood-smear morphology with complete blood count variables, patient age, symptoms, or other laboratory measurements when ethically and clinically appropriate. Multi-modal models may improve discrimination when morphology is ambiguous, but they also introduce missing-data and interoperability challenges. A simple, well-validated image model can be preferable to a complex multi-modal model if the additional inputs are inconsistently available.

The design should therefore start from the clinical question rather than the availability of algorithms. If the intended use is smear triage, image data may be sufficient. If the intended use is subtype classification or risk stratification, additional clinical and molecular data may be required. Each added modality should demonstrate incremental value over a simpler baseline through prespecified analysis.

Q. Uncertainty and Abstention

A clinically useful AI system should be allowed to abstain when it encounters an uncertain or unfamiliar case. Conventional classifiers always select a class, even when the input falls outside the training distribution. Confidence thresholds, out-of-distribution detection, or uncertainty-estimation methods can instead route low-confidence cases directly to expert review. This is especially appropriate in hematology, where rare morphologies and artifacts can differ substantially from curated training data.

Abstention creates an important evaluation trade-off between coverage and reliability. Researchers should report the proportion of cases for which the model provides a prediction and the performance achieved at different confidence thresholds. A system that accurately assists on 80% of routine cases and safely defers the remaining 20% may be more clinically useful than a model that attempts to classify every case with poorly calibrated confidence.

R. Clinical Workflow Scenario

One realistic workflow is AI-assisted pre-screening. After a digital blood smear is acquired, the system identifies candidate abnormal cells and presents them in a ranked review queue. The laboratory professional examines the highlighted regions, confirms or rejects the suggestions, and records a decision. The AI output does not create the diagnosis; it prioritizes visual review and may reduce time spent searching large fields. Cases with high uncertainty or discordant findings proceed through normal expert review and confirmatory testing.

This workflow is compatible with the professional perceptions observed in the survey, particularly favorable views of diagnostic speed, monitoring, and decision support. It also

limits the risk of automation bias because the human reviewer remains responsible for interpretation. Future clinical research can compare review time and error patterns with and without AI assistance while keeping the diagnostic reference process unchanged.

S. Economic and Operational Evaluation

Clinical adoption also depends on operational feasibility. Deep-learning systems require hardware, software maintenance, model monitoring, cybersecurity controls, and staff training. A future Oman study should estimate the cost of image digitization, inference infrastructure, validation, and ongoing governance rather than considering algorithm accuracy in isolation. Benefits should likewise be measured in operational terms such as time saved per smear, reduction in repeat review, or ability to prioritize urgent cases.

Economic analysis should not assume that faster classification automatically lowers cost. If an AI system generates many false alerts, requires extensive manual correction, or depends on expensive imaging infrastructure, total workload may increase. A prospective pilot should therefore collect workflow time, number of manual interactions, system downtime, and maintenance burden alongside diagnostic metrics.

VII. LIMITATIONS

The primary survey is small (N=32) and measures perceptions rather than clinical outcomes. The professional distribution is useful but does not substitute for a representative national sample. The study is cross-sectional, so familiarity and positive attitudes may influence each other in either direction. Some technical performance values in the source report originate from heterogeneous published studies and public datasets rather than a single reproducible local experiment, making direct model comparisons inappropriate unless datasets and protocols are harmonized. Finally, no prospective Oman-based clinical validation is reported.

VIII. CONCLUSION AND FUTURE WORK

AI has substantial potential to support blood cancer detection, particularly through automated analysis of blood-smear images and other hematology data. The surveyed healthcare professionals were generally receptive to diagnostic-speed, monitoring, and decision-support applications, and prior AI experience was associated with more favorable perceptions. These findings support further investigation but should not be interpreted as proof that an AI system has already improved patient diagnosis in Oman.

The next stage should establish a reproducible local validation pipeline: curate representative patient-level data, benchmark transparent and deep-learning models under the same protocol, report clinically meaningful metrics and calibration, perform external validation, and prospectively evaluate workflow integration. AI should remain a decision-support technology under professional oversight. A publication-quality contribution in this domain is therefore not the highest isolated accuracy figure, but a transparent chain of evidence showing that a model is accurate, robust, fair, understandable, and safe in the setting where it will actually be used.

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Design Requirements for an AI-Based Personalized Learning System for First-Year Calculus: A Mixed-Methods Study

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Abstract—Although AI can enable adaptive and personalized instruction, the design of useful systems requires insight into students' challenges, support preferences, and expectations towards feedback. This paper examines students' needs regarding an AI-powered personalized learning system in first-year Calculus I at the University of Technology and Applied Sciences (UTAS) in Oman. Using mixed methods, we combined a general needs questionnaire (n = 71), presentation/study preference questionnaire (n = 42), and semi-structured interviews (n = 8). By applying descriptive statistics and exploratory analysis, difficult calculus topics, learning format preferences, and support expectations are identified. Integration (33.8 %), derivatives (25.4 %), and limits (19.7 %) were ranked as hardest topics. While visual presentation yielded the highest mean value (M = 11.78, SD = 2.43), no modality had more than 40 % preference votes, which questions strict learning-style taxonomies. Students generally agreed on receiving immediate feedback, step-by-step solution explanations, gradually increasing difficulty, hints, and self-paced learning. These insights are discussed and translated into design requirements for human-in-the-loop adaptive architecture coupling learner modeling, error-aware feedback/response generation, mastery tracking, and multimodal explanation capabilities. As this work does not include controlled study data but leverages existing cross-sectional self-report data from students, this paper does not make claims regarding improved academic performance but identifies evidence-backed requirements and future-proof success measures for an experimental version of the proposed system. Paper ID 6087874

Keywords—artificial intelligence in education; personalized learning; adaptive learning; Calculus I; intelligent tutoring systems; higher education; mathematics education

I. INTRODUCTION

Calculus I serves as a prerequisite for many degree programs in science, technology, engineering, computing, and mathematics (STEM+C). Students learning university-level limits, derivatives, and integration often experience conceptual hurdles and procedural difficulties as they adapt to college-caliber mathematics. This difficulty arises rarely if ever uniformly; students arrive with varied prerequisite knowledge, study habits, confidence levels, pacing needs, and preferred explanatory styles. Consequently, any single instructional sequence will oversupport some learners while repeating too much content for others. Intelligent educational systems driven by Artificial Intelligence (AI) provide technical leverage for meeting each student "where they are". According to a systematic review of 146 articles focused on higher education applications, the dominant AIEd themes are adaptive systems and personalization, intelligent tutoring systems, assessment and evaluation, and profiling/prediction [1]. Follow-up reviews have made a stronger case for AI-supported personalization in structured domains like STEM+C while cautioning that effective systems depend on sound instructional design as well as data quality and responsible use rather than automation for its own sake [2]. Calculus lends itself to human-in-the-loop AI because mathematical errors frequently indicate specific misconceptions or points of procedural breakdown. At a high level, AI could enable an environment to diagnose response patterns, choose appropriately difficult examples, provide hints prior to full solutions, and update explanation modes as mastery is demonstrated. Wei et al. recently integrated ChatGPT, MathGPT, Gemini, and Wolfram Alpha into a calculus classroom and reported opportunities for personalized feedback and increased student engagement, but students were also able to bypass subject matter limitations through partial inspection of AI tools and teachers played a critical role in mediating their use [3]. The current study takes a different approach to this challenge by collecting student data to inform design decisions instead of evaluating a deployed tutor. The source article contains proposed comparisons of AI-based and traditional study practices, but these comparisons are not reported on because the data collection contained questionnaires and interviews rather than a clearly defined randomized or quasi-experimental study of achievement. This paper only discusses findings that can be directly traced to the collected data and considers achievement testing as future work.

A. Research Objectives

Identify important considerations for the design of an AI-enabled learning environment intended to support Calculus I at UTAS. This goal will be accomplished by: (1) determining which Calculus I topics students find most difficult; (2) gathering qualitative information on students' preferred forms of explanation, feedback, pacing, and representation; (c) investigating students' attitudes towards AI-supported personalized learning environments; and (d) translating these findings into actionable design recommendations for both an adaptive-learning architecture and an evaluation plan.

B. Research Questions

RQ1: What topics in Calculus I do UTAS students find most difficult? RQ2: How do students prefer to receive instructional support? RQ3: Are students open to receiving personalized learning support from AI? RQ4: What components must be developed to turn these needs into an adaptive learning environment that is both safe and pedagogically useful?

II. RELATED WORK

AI-supported personalization continues to grow from prior work on intelligent tutoring and adaptive-learning systems toward complex, data-enabled technologies that monitor performance and change course. Zawacki-Richter et al. reviewed literature focused on AIEd applications in higher education and found adaptive systems/personalization to be the most common category, but criticized much of this research for having weak pedagogical grounding and addressing ethical concerns [1]. These critiques are worthwhile bringing forward because offering personalized recommendations is not trivial; an effective system must make pedagogically justifiable decisions about what to explain, when to intervene in group settings, and when students might benefit most from instructor guidance. Generalized evidence

on personalized learning supports its value but leaves the question of how open. RAND's synthesis of personalized-learning school performance found encouraging patterns on average in mathematics and reading, but their sampled schools exhibited notable variation in implementation fidelities [4]. In work more specific to STEM+C disciplines, Zhang et al. recently found that AI-enabled personalized education can have positive effects on learning outcomes, but that effect sizes vary according to the educational level studied, type of tool used, instructional strategies employed, and implementation supports [2]. This analysis suggests that careful local validation is necessary instead of adopting a feature and hoping it will aid learning. There is some calculus-specific evidence as well. Torres-Peña et al. demonstrated the use of several generative and otherwise AI tools as part of classroom activities for learning calculus, including how AI can aid in explanation, problem generation, and feedback, though their methods for procedural-error detection were imperfect [3]. Putthidech et al. used PLS-SEM to study users' perceptions of AI-based learning in a calculus course and found that perceptions of adaptivity, feedback accuracy, trust, and perceived pedagogical value were associated with cognitive-emotional reaction and learning outcomes though together their model accounted for 75.7% of the variance in outcomes [5]. These findings speak to the efficacy of adaptivity and trustworthiness (in feedback), though causation cannot be drawn from this cross-sectional study. Research on intelligent tutoring in mathematics can also serve as a reference. Meta-analysis has shown that intelligent tutoring can aid math learning, particularly when tutors allow for guided practice, provide feedback, and adapt the sequence of material presented [6]. Personalization in the proposed Calculus I system should therefore be based on students' demonstrated performance and mastery, not static labels.

A. A Note on "Learning Styles"

The original study categorized preferences into visual, auditory, reading/writing, and kinesthetic (VARK) groups. Published with permission, scores on this instrument are presented here as indicative of students' reported presentation preferences, not fixed learning styles. The four mean scores are relatively close together. Designing activities based on this taxonomy is risky; instead, a safer course of action is multimodal personalization: present students with graphs, symbolic derivations, worked examples, verbal explanations, and interactive practice opportunities, while also adapting the mixture of activities to the needs of the task, student preference, and performance.

B. Research Gap

Little work targets the needs of first-year Calculus I students specifically in Oman. Related work often measures broad acceptance of AI in education or evaluates specific tools. Those tools often lack specificity around how learner data, misconception diagnosis, adaptive sequencing, feedback, and instructor supervision ought to work together in the context of a system designed specifically for calculus. We close this design gap by surveying students about difficulties, teaching preferences, and qualitatively interviewing them to better inform a context-specific architecture.

C. Adaptive Feedback and Scaffolding

Feedback is among the most prevalent mechanisms reported in intelligent and adaptive math environments. One meta-analysis of human-machine feedback found within smart learning environments demonstrated both positive effects on learning processes and learning outcomes. This research also demonstrated an effect of direction, form, and technique on feedback outcomes [7]. This distinction is critical for Calculus I since feedback may serve different purposes. Verification feedback could communicate right or wrong; elaborative feedback could communicate where in the problem the student made an error; and scaffolded feedback could provide the student with a hint or guiding question that still requires the learner to complete the solution. As such, a personalized calculus environment should not treat all incorrect answers equally. Recent literature reviews focusing on adaptive and personalized math learning programs echo these mechanisms, identifying feedback, adaptive activities, on-demand hints, tutoring, mastery-based sequencing, and learner-status monitoring as commonly reported system features [8]. These categories imply personalization functions at multiple levels. Content personalization dictates which example or concept is shown; difficulty personalization determines the complexity of follow-up activities; feedback personalization determines amount and type of assistance given; and pacing personalization dictates when a student should review material, continue working, or move forward. The architecture proposed in this paper reflects these levels of personalization without enforcing one method of instruction as ideal for all students.

III. METHODOLOGY

A mixed-methods, cross-sectional design combined two quantitative questionnaires with semi-structured interviews. This approach was appropriate for requirements discovery because the quantitative data identified recurring patterns, while the interviews provided contextual information about students' experiences and expectations.

A. Participants and Sampling

Study participants were university students with prior or current Calculus I experience recruited via convenience sampling. Ninety-one participants responded to the general questionnaire, 42 responded to the presentation/study preference questionnaire, and eight students participated in semi-structured interviews. The sample sizes are unequal because they represent different data- collection exercises and are reported separately rather than pooled.

B. Data Collection

General questionnaire included questions about challenging topics in calculus and about attitudes towards artificial intelligence integration. Preference questionnaire items were 5-point Likert-type and considered visual, auditory, reading/writing, and kinesthetic categories, interpreted below solely as descriptive preferences. Interviews asked about difficulties learning calculus, calculus motivation, experiences with artificial intelligence tools and what sorts of support respondents would want (e.g., surface-level explanations vs. support diving deeper).

C. Analysis

Quantitative Answers: Frequencies, Percentages, Means, Medians, Standard Deviations Interview Data: Content analysis around themes of learning difficulty, motivation, AI

competency and preferred system behavior. Pre/post achievement-controlled data set, group assignment method, test statistic degrees of freedom, or raw group experimental N-Series scores were not found in the reported study. Therefore, the independent-samples t-test, ANOVA, and Pearson r values presented in the source document are not being cited as supporting evidence in this publishable article.

D. Ethical Considerations

Consent was voluntary. According to the study's documentation, participants were told the purpose of the research, that personal identifiers were not being collected, and that data from surveys and interviews would be used for educational purposes. One thing to consider for a future deployment that includes logging of fine-grained student performance would be addressing privacy concerns such as data minimization, access control, retention, model interpretability, and instructor oversight of automatic decisions.

E. Requirements-Engineering Procedure

Since this work takes a requirements-driven approach, results of the survey/interview were framed as system requirements instead of merely demographic/educational information. Generally, a requirement was elevated to high-priority status if it addressed a trend among student struggles, common preferences, or safety/pedagogical concerns from the literature. These requirements were categorized into four buckets: learner-model requirements, instructional requirements, interaction requirements, governance requirements. This framework ensures there is a clear connection between the expressed needs and the design of the proposed system.

Learner-Model Requirements: Keep track of concept-level mastery, recent failures, velocity, and history of support. Instructional Requirements: Gradually increase problem difficulty, allow review of prerequisite material, provide explanations in multiple formats, encourage practice on trouble spots. Interaction Requirements: Give feedback immediately but gradually, allow student to request hints, make it clear how far student is into problem, allow student to control which representation is seen. Governance Requirements: Allow instructor visibility into usage, limit customer data stored, allow AI to explain confidence in its knowledge, escalate when system cannot validate a mathematical answer. These final requirements can be used to create software user stories and acceptance requirements when prototyping begins.

IV. RESULTS

A. Perceived Difficulty of Calculus Topics

In the general questionnaire integration was reported as the hardest topic by 33.8% of users followed closely by derivatives at 25.4% and limits at 19.7%. From this data we can conclude that the adaptive system should focus heavily on integration but should continue to diagnose for understanding in prerequisite topics.

TABLE I. SELF-REPORTED CALCULUS DIFFICULTY

Topic	Percentage	Recommended Focus
Integration	33.8%	Worked examples, prerequisite knowledge, and support in selecting the correct method
Derivatives	25.4%	Link graphical interpretation to symbolic manipulation
Limits	19.7%	Conceptual understanding, visualization, and prerequisite knowledge review
Other topics	21.1%	Continue broad diagnostic assessment

B. Presentation and Study Preferences

The mean score was highest for visual presentation (M=11.78, SD=2.43) followed closely by reading/ writing (M=11.39, SD=2.39), auditory (M=11.35, SD=2.35), and kinesthetic (M=11.30, SD=2.30). These means were close together, suggesting that students should not be forced into singular modalities.

TABLE II. DESCRIPTIVE PREFERENCE SCORES

Learning Style	Mean (M)	Median	SD
Visual	11.78	12	2.43
Reading/Writing	11.39	12	2.39
Auditory	11.35	12	2.35
Kinesthetic	11.30	12	2.30

Students mentioned similar attributes across both surveys and interviews. The attributes they described were less abstract than just a modality label: go through problems step by step, begin with easier problems and move to harder, give feedback right away, give hints before showing full answer, and work at one's own pace.

C. Attitudes Toward AI-Supported Learning

The overall questionnaire revealed general positive perceptions of AI-supported Calculus I learning. Students anticipated AI could aid with studying, instant feedback, and flexible learning. Interviews supported personalized explanations and adaptivity. These responses are acceptance/design-preference evidence, rather than evidence of improved learning.

D. Synthesis of Empirical Requirements

Together, these findings argue against using a single personalization heuristic. Instead, they support a hierarchy of requirements. First, the system should understand what math topic is being learned, and what the student's current mastery level is. Second, the system should understand what kind of difficulty the learner is experiencing: is it a prerequisite gap, or conceptual confusion, or algebra error, or misapplication of procedure? Third, the system should provide an appropriate intervention: a visual explanation, worked example, brief prerequisite exercise, on-demand hint, or easier problem of similar type. The student's response to this intervention now serves as evidence to update their mastery estimate.

This evidence-driven approach seems preferable to pigeonholing students as visual, auditory, read/write, or kinesthetic learners. Their self-reported preferences can still be used to shape interface options. However, the primary method of adaptation should come from observed learning behavior. A student may initially prefer graphical explanations, but after practice with differentiation problems may find symbolic derivations more helpful. Personalization is thus framed as an ongoing decision-making process.

V. PROPOSED AI-BASED PERSONALIZED LEARNING ARCHITECTURE

The results from the user study and discussion of related work led us to propose a human- in-the-loop system architecture with the following six system components: learner profile including prerequisites mastery and interaction history, diagnostic engine for identifying conceptual and procedural errors, mastery model for determining whether the student should advance, an adaptive selector to determine which explanations to show and what practice problems to assign, feedback engine that determine whether to offer hints, show intermediate steps, or provide full worked out solutions, and instructor dashboard to allow instructors to monitor student progress and intervene when necessary. TABLE III. PROPOSED SYSTEM COMPONENTS Learner profile — Determines student’s mastery of prerequisites, pace, preferences, and prior interaction history Diagnostic engine — Determines which concepts and procedures the student errored on Mastery model — Predicts whether student is ready to move on Adaptive selector —Determines what items to show the learner for what content, in what modality, and at what difficulty Feedback engine —Determines whether to give hint, intermediate steps, or provide full explanation Instructor dashboard — Allows for human monitoring and intervention

A. Personalization Logic

The initial working version can be completely rule-based; it does not have to use a neural network. Thresholds for mastery on rules or decision trees that are easy to interpret could translate performance patterns into tutoring actions. Frequent substitution errors on integration can prompt review of prerequisite material; procedural correctness with conceptual explanation errors can prompt a graph interpretation problem; blazing through several items could escalate difficulty. As more data is accrued, predictive models can be benchmarked against heuristics.

B. Feedback and Trustworthiness

Feedback must be conditioned by didactic limitations. The system should err towards providing hints, leading questions, and worked-verification steps as compared to unsupported final-answer production. Math input should be verified by a symbolic engine where possible, and low-confidence answers should be deferred to the teacher. This speaks directly to alleviating the procedural-error restrictions found in AI-assisted calculus learning [3].

C. Evaluation Framework

The future study should include both AI-supported condition and a matched control condition that use the same assessment tool and learning period of time. Outcome measures should consist of pre/post conceptual learning and retention after a delay as primary outcomes. Time on task, hint frequency, engagement, perceived usefulness, and cognitive load should be considered as secondary outcomes. Accompanying sample sizes, means, standard deviations, effect sizes, confidence intervals, assumptions, and exact p-values should be reported.

D. Learner Model and Mastery Representation

The learner model serves as the primary knowledge representation in our proposed system. At a bare minimum, it should track concept-level mastery for limits, continuity, differentiation, applications of derivatives, integration, and prerequisite algebra. Concept mastery can be operationalized as a score that gets updated when a student answers a formative question. The learner model should also track recent mistakes categories, number of hints used, response time, and degree of scaffolding needed.

These variables have a more direct relationship to learning than do broad demographic variables and are thus better targets for personalization. In its simplest form, mastery could be incremented using heuristic rules. For example, several consecutive correct answers with few hints could increase mastery. Making the same mistake multiple times or using numerous hints could initiate review. Later iterations could consider assessing Bayesian knowledge tracing, performance-factor analysis, or another transparent learner-modeling technique. Whatever predictive model is chosen should be benchmarked against a naïve baseline and assessed for calibration as well as accuracy. An overconfident estimate of mastery could lead the system to promote a learner who has not yet acquired the prerequisite knowledge.

E. Misconception-Aware Diagnostic Layer

A calculus tutor needs to be able to differentiate between a wrong answer and the thought process that led to that answer. Two students could reach the same incorrect answer through distinct mistakes: one student may have applied the chain rule incorrectly, while another knew the chain rule but made a mistake simplifying their answer. The underlying diagnostic layer should verify intermediate steps wherever possible. Transformations can be checked using rule-based symbolic analysis, while an AI explanation system can classify the most likely misunderstandings and produce an instructor-ready response. Regardless of their power, the system should not use an unchecked language model as the final arbiter of mathematical correctness. Research conducted in calculus classrooms this year has found that while generative AI tools can offer students instant customized assistance, they sometimes miss procedural mistakes [3]. A more responsible deployment would use deterministic mathematical verification in conjunction with AI-produced explanations. If the verifier and language model produce conflicting results, or if the

verifier flags an error but has low confidence, the system should flag the response for instructor feedback instead of presenting a potentially wrong explanation to students as fact.

F. Adaptive Sequencing and Scaffolding Policy

Adaptive sequencing decides what the learner should see next. A simple but effective policy will define three zones: remediation, consolidation and progression. Remediation applies when prerequisite misconceptions reoccur; consolidation allows further practice at the current level; and progression presents new problems above the current level after performance has stabilized. Even within each zone the system can vary the representation of material and the degree of scaffolding provided. After the first error the system may show a short hint. After a second error it may state the relevant principle. After a third error it may show a partially worked solution then present a new problem requiring independent solution.

This graduated assistance is designed to help students without falling prey to two extreme pitfalls: too little support or answer dependency. One 20/group of studies conducted a systematic review of AI-based math tutoring and found broadly encouraging patterns of achievement, but also noted variation in effectiveness across implementation settings and a relative lack of direct evidence for gains from generative AI by itself [9]. Another recent survey of AI-powered personalized math learning highlighted dependence on hints and mismatched adaptivity as possible limitations [10]. For these reasons, the system we propose provides assistance as a scaffold to be slowly removed.

G. Instructor Dashboard and Human Oversight

The instructor dashboard isn't an administrative tool—it's an extension of the teachable machine's control interface. Ideally, it would give instructors an overview of class-level and student-level mastery, flag concepts with unexpectedly high error rates, surface students who consistently need help, and highlight examples of AI-generated feedback that were produced with low-confidence. Instructors would be able to override mastery estimates, turn off inappropriate generated content, assign remediation practice, and review the artifacts that contributed to a particular recommendation.

On a class-wide level, aggregated data can help instructors identify if a challenge is common or individual to only a few students. If many students are making the same mistake on integration problems—say they don't understand substitution—the instructor might decide to review the concept during class time instead of having the teachable machine tutor address the challenge one student at a time.

H. Privacy, Fairness, and Responsible Use

Personalized learning needs data, but doesn't need data about students beyond what is necessary for education. The prototype should not collect data about protected personal attributes without a specific research or accessibility goal. Wherever possible, student identifiers should be separated from analysis records, access to data should be role-based, and retention periods should be established prior to system launch. Students should be notified when they are receiving feedback from AI, and provided a pathway to ask for instructor feedback. Considerations of fairness should be included in validation. Even a model with high average performance may yield weaker mastery estimates or less actionable feedback for students with lower prior preparation, diverse language backgrounds, or novel solution approaches. Validation should therefore test for disparities in errors and benefits across relevant populations, but should not make demographic comparisons without supporting evidence of group differences. Personalization responsibly seeks to adapt instructional support to demonstrated need, not infer ability from identity.

VI. DISCUSSION

Although the study's clearest contribution may not be evidence that their AI system raises grades, it is a better specification of what a helpful Calculus I AI system should do. The authors identify three primary design focuses based on student performance data. Calculus personalization should be topic-sensitive and weighted toward integration and derivatives. Students clearly prefer process-oriented scaffolding including immediate feedback, hints, stepwise explanation, progressive difficulty, and self-paced learning. Personalization can and should still be multimodal, but should not pigeonhole students into learning-style categories. These findings coincide with a larger body of AIED literature. Adaptive and intelligent tutoring systems "are best justified when they are sensitive to the learner's state as evidenced by his or her performance" rather than using cursory methods of personalization [1], [6]. Torres-Peña et al.'s data explain part of why human oversight cannot be removed from tutoring systems yet: a general-purpose AI could successfully drive explanation and improve learner engagement but still miss some types of procedural mistakes [3]. Putthidech et al. find that adaptability, quality of feedback, trust, and perceived pedagogical value all affect calculus-specific AI adoption [5]. With these insights in mind, UTAS and other Omani universities have a clear path to implementing a personalized learning technology. By automating tedious diagnosis and low-level practice, the system can surface trends to better inform instructors where to focus their intervention. As this role keeps instructors in the teaching loop, it also supports the aims of Oman Vision 2040's focus on education, innovation, and digital government [7].

A. Implications for Calculus Instruction

Taken together, these findings point to AI personalization being most useful when it augments sound instructional practice. The system may offer frequent low- stakes practice outside of class time, but the lecturer is responsible for framing the problem conceptually, designing assessments, and intervening when students form long-term misconceptions. This blended role meshes with studies finding that intelligent tutoring can have a positive effect, but that results vary widely in practice. One 2016 meta-analysis combined results from 50 controlled studies and found intelligent tutoring improved student performance by a median of 0.66 standard deviations. That review also found that measured effect sizes were dependent on the degree to which instruction and assessment were aligned [11].

Results for individual commercial adaptive math platforms have also produced mixed results. A meta-analysis focused on ALEKS usage in K-12 and higher education settings found its effectiveness was broadly comparable to traditional instruction. ALEKS was more effective when used as a

supplement to traditional instruction rather than a replacement [12]. This finding further justifies the design choice made in this paper to frame the proposed Calculus I AI as an adjunct to traditional lecturers.

B. Implications for UTAS and the Omani Context

For UTAS, such a pilot implementation might focus on one or two large-enrollment sections of Calculus I and a small subset of concepts, rather than deploying full-course automation. Integration would be a natural place to begin development because it was the topic with the highest number of mentions in the difficulty survey. Initial functionality could include support for diagnostic quizzes, step verification, hints, worked-example retrieval, and instructor analytics. Constraining the scope initially would allow time to assess usability, mathematical accuracy, and data-governance workflows prior to scaling up. Local infrastructure also opens the door for bilingual or language-aware support. While math notation is mostly language independent, supporting students who must learn technical material in their second language creates an additional cognitive hurdle if explanatory text is not also available in Arabic. It would be worthwhile for a future system to measure if succinct English explanations, supplemental Arabic clarification, or glossaries of terms affect student understanding without diminishing the mathematical rigor of the course. Such features should be empirically tested rather than presumed helpful.

VII. LIMITATIONS

The convenience samples limit representativeness. Also, the general survey (N=71), the preference survey (N=42), and the interviews (N=8) do not combine to make one matched set of data. The responses are self-reported and may indicate perception more than actual observed learning behavior. The preference categories were used as learning styles for the purpose of the source report, but should not be thought of as rigidly defined cognitive types. Finally, and most crucially: we have no gold-standard adequately documented controlled intervention upon which to base causal claims about grades. As such, the findings below support system requirements and hypotheses to be tested, not conclusions that the proposed AI system has improved grades.

VIII. CONCLUSION AND FUTURE WORK

We report on a mixed-methods needs-analysis that elicits student-focused requirements for an AI-powered personalized learning environment to support first-year Calculus I students at UTAS. Integration, derivatives, and limits were recurring topics students found challenging; students also expressed preferences for immediate feedback, step-by-step explanations, scaffolding, hints, self-paced learning, and multimodal display of information. Learners' reported attitudes towards AI were mostly positive, indicating a willingness to accept AI-enabled support if it proves beneficial and trustworthy. The follow-up development phase should focus on the implementation of a system prototype that incorporates learner modeling, misconception-informed diagnosis, adaptive sequencing, limited answer disclosure, and instructor monitoring. This should be coupled with a pre-registered quasi-experimental or randomized controlled study to measure effects on conceptual learning, knowledge retention, engagement, and cognitive load with clear statistical reporting. Long-term prospects can include measurement of privacy, bias, accessibility, hallucination/error rate, and whether personalization features help bridge the gap for students of varying mathematical backgrounds.

A. Proposed Experimental Validation

A subsequent validation study would benefit from enrolling many more students and using a pretest-posttest design. Participants could be randomly assigned to an AI-supported condition and comparison condition in which they receive the usual course materials. Ideally the same validated conceptual assessment would be given before and after the course, with a delayed test administered for the purpose of studying retention. Although random assignment would be best, this may not be possible in all implementations. When this is the case, it is important to at least report baseline equivalence and include relevant covariates. In addition to testing for achievement, the evaluation should include measures of system use and other learning process variables. This can include number of problems attempted, hints requested, time on task, mastery level transitions, frequency of repeated misconceptions, instructor override, etc. Usability can be measured with a validated instrument, and qualitative interviews could assess when students found AI help was useful, confusing, too much, or too little. Collecting this data would allow researchers to test not only if the system is effective, but how and for whom.

B. Technical Validation

Diagnostic accuracy should be assessed independently of pedagogical value. An adjudicated gold standard of calculus solutions should be created with correct work, common misconceptions, algebra mistakes, and partial work. This data set can then be used to measure performance of the diagnostic layer. Accuracy metrics may include error localization precision and recall, agreement with gold labels, false negative rate, and the fraction of feedback flagged for instructor review. Latency, uptime, and cost per session should be tracked as well. Even a perfect solution would be useless if it cannot operate at scale in a timely manner or within budget.

C. Illustrative Personalization Scenarios

Several realistic learning examples help demonstrate the proposed architecture. First, consider a limits example where a student may know how-to plug-in values to routine problems but panic when faced with an indeterminate form. The diagnostic engine determines that the student knows substitution but hasn't yet chosen a strategy for working with limits. Instead of displaying the entire solution, the tutor may first quiz the student about the indeterminate form and then give them a graphical view of the function around the limit value before providing a similar practice problem. If the student independently solves the problem, then their mastery estimate for this skill would go up.

Second, imagine that a student performing differentiation frequently forgets to take the derivative of the inner function when using chain rule. Since the same mistake is made with many different expressions, the system can infer that this is likely a procedural misconception instead of an isolated arithmetic error. The initial intervention could draw attention to the nested functions; the next intervention could ask students to annotate which is the outer and inner function; and

a subsequent intervention could reveal part of the derivative. The key idea is that the system flexibly adjusts the level of support to maintain the learner's cognitive engagement with the solution.

A student could be aware of multiple techniques for integration but choose poorly. The tutor could ask diagnostic questions about the makeup of the integrand prior to suggesting a technique. Given that integration was reported as the most difficult topic in this survey, a prototype should at least have an adequate collection of examples using substitution, integration by parts, partial fractions (where applicable), and interpretation of definite integrals. Course-specific or high-stakes examples should pull from instructor-authored problems.

D. Content Quality and Knowledge-Grounding Strategy

Of course, a system proposal suitable for publication also includes a plan for quality control of instructional content. The prototype should continue to store curated course notes, definitions, worked examples, assessment goals, and human-reviewed explanations. When generative AI is incorporated, retrieval from this database can limit the response to information relevant to the Calculus I curriculum. This helps prevent the chance that a well-worded but inappropriate explanation may use notation, methods, or vocabulary that were never taught during the course.

AI-generated exercises should undergo automated and human review for quality. At a bare minimum, the system can check that a problem is valid (i.e. solvable), that the stored answer is mathematically accurate, and that the difficulty matches the target learning goal. Newly created automated items can be routed to a review queue by default, and not made visible to students until approved by a lecturer. Long term item statistics (completion rate, discrimination, common student errors, average hint requests) can help identify questions that are too easy, too hard, unclear, or not helpful.

E. Success Criteria for a Future Prototype

A successfully working prototype in the future should meet several criteria along educational, technical, and user-experience axes. Educational criteria include gains in conceptual understanding, appropriate loss of repeated misconceptions, and proof that students can solve follow-up problems with minimal support. Technical criteria include correctness of mathematical verification, reliability of logging, appropriate response latency, and stability under high loads of simultaneous students. User-experience criteria include perceived usefulness, understandability of feedback, ease of navigation, and understandability of the system's explanation for recommending an action.

One metric should not make or break a decision on the system's usefulness. For example, a tutor could potentially maximize user-satisfaction ratings by immediately providing students with full answers, but doing so is counterproductive to learning. On the other hand, a system could lead to strong learning gains but if it is too difficult for lecturers to use to make problem setup it will not be used for everyday course problems. Evaluation of the tutor should look at trade-offs between learning effectiveness, independence, user-friendliness, instructor workload, accuracy, and operational expense.

F. Threats to Validity in the Planned Evaluation

Several threats are worth anticipating before moving to a next-stage experiment. For example, selection bias is possible if students who opt to work with the AI tutor differ from others (e.g., by being more motivated or comfortable with technology). Testing effects are possible if pretests, practice activities, and posttests include the same or very similar questions. Novelty effects are possible if students work harder or more consistently with the system simply because it is new. Comparison-group students may also be “contaminated” if they receive AI-generated explanations from classmates or use external generative-AI tools while participating in the study. Most of these risks can be mitigated with careful study design. Randomization or matched comparison groups can mitigate selection differences; parallel forms of assessment can mitigate repeated-test effects; a longer intervention can help differentiate novelty effects from those of sustained use; and study instructions can specify whether participants are permitted to use external tools. Transparent reporting of attrition and missing data is also critical. Rigorous application of such procedures is required before a later study can move beyond the exploratory design evidence described here and begin to make defensible claims about learning effectiveness.

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Beyond "Brain Rot": Short-Form Digital Content Consumption, Attention, and Academic Focus Among UTAS Students

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Abstract—Platforms for short-form video viewing are now habitual in university students' daily media consumption. Such high frequency of use poses questions of prolonged attention, academic distraction, and self-regulation. This research sought to assess University of Technology and Applied Sciences (UTAS) students' usage of short-form digital content, as well as student self-reported attention span, concentration, academic focus, digital consumption habits, digital literacy, and desire to implement healthy boundaries with digital media. Methods: The study was quantitative in nature, employing a cross-sectional correlational design with a sample of 200 UTAS students. Students were administered a survey via online questionnaire, featuring five-point Likert-scale items. Results were descriptively analyzed and are reported via frequencies and percentages. Most participants identified as male (n=169, 84.5%) and were between the ages of 20–30 years old (n=167, 83.5%). Students reported high usage of short-form content, with 83% strongly agreeing/agreeing that they spend "a lot of time watching short form videos" each day and 87% strongly agreeing/agreeing that they "look at short-form content several times a day". Self-reported cognitive and academic impacts were prevalent; 54% of students agreed that their attention span had "gone down because of [their] phone" while 79% strongly agreed/agreed that they "have a hard time studying without looking at [their] phone". Students also reported awareness of potential attention consequences (78% strongly agreed/agreed with this statement) and desire to limit their short-form content consumption to better their focus (80% strongly agreed/agreed with this statement). Limited by its cross-sectional, self-reported nature and lack of reported correlation coefficients and p-values, no causal or statistically significant conclusions can be drawn from this study. Instead, this paper discusses "brain rot" as a culturally pervasive term rather than a medically recognized term and encourages future objective measures of attention, digital self-regulation efforts, and longitudinal studies in Omani higher education.

Keywords—short-form video; brain rot; attention span; cognitive function; academic focus; social media; digital well-being

I. INTRODUCTION

Short-form video apps have changed the pace of digital media. They blend succinct audiovisual clips with algorithmic feed curation, infinite scroll, and rapid-fire delivery of new stimuli. TikTok, Instagram Reels, and YouTube Shorts stand out among short-form apps because they can be loaded again and again while students study, commute, socialize, or unwind. Concerns for students' academics center not on short-form videos themselves but on high-volume, habitual use that smashes commas in attention. Enter Text

Uttered frequently as an internet meme, "brain rot" was Oxford Word of the Year 20 24. It is colloquially defined as zapping will or intelligence after watching too much low-effort media [1]. For clarity, this study does not equate brain rot to any specific psychological disorder. Researchers have begun to measure similar phenomena with constructs like cognitive load, cognitive fatigue, problematic media use, attentional control, and behavioral addiction. 2 , 3 A 20 26 qualitative study on college students' experiences described "brainrot" as a perceived decline in productivity and focus after consuming low-effort digital content, without framing it as a diagnosable condition [4]. Enter Text

This survey research was conducted with students at UTAS in Oman. Its value lies in its regional focus. Studies on short-form video are abundant, but most skew toward countries with high smartphone penetration. This research attempts to close the gap by studying a population of students who are known to have high exposure rates to mobile media but are currently underrepresented in short-form literature. We wanted to know if self-reported increases in short-form video consumption were matched by perceived declines in attention, concentration, academic focus, and digital habits. We also wanted to know if students were aware of these risks and if they would be willing to change their media consumption habits.

A. Research Objectives

The objectives of this study were to: 1) measure and describe engagement with short-form media; 2) identify self-perceived inattentiveness due to short-form media use; 3) measure perceived academic distraction and frequency of checking phones; 4) identify behaviors associated with high levels of short-form engagement (such as task-switching and wanting to check short-form media); 5) determine students' awareness of the effects too much scrolling can have on attention; and 6) determine students' openness to implementing small habits to self-regulate technology use.

B. Research Questions and Hypothesis

RQ1: What is the consumption frequency of short-form digital media among UTAS students? RQ2: Which issues with focus and attention do students attribute to short-form content? RQ3: How do students feel short-form affects their attention in school? RQ4: What patterns of behavior are prevalent among high consumption students? RQ5: How conscious are students of possible effects and willing to modify their behavior?

The authors of the original study tested H0: There is no relationship between excessive consumption of short-form digital media and cognitive function and attention span in college students and H1: There is a relationship between excessive consumption of short-form digital media and cognitive function and attention span. For this publication-ready version, we interpret the hypothesis conservatively as we were only given the labels of directional relationships from the provided report and not values for coefficients, confidence intervals, or p-values.

II. RELATED WORK AND CONCEPTUAL FOUNDATION

Prior findings from digital media and cognition suggest that effects are contingent on what individuals do online (e.g., short videos vs. reading news articles), how frequently they use certain applications or services, and context in which media are used. This potential nuance was highlighted by Firth et al., who wrote that "effects of Internet use cannot be boiled down to whether Internet use is harmful or beneficial. Characteristics of the individual, the content being used, how it is being used, and what social contexts the individual is embedded in will influence cognitive and psychological outcomes…" [5]. In short, these articles highlight the importance of considering different activities within the broad label of "screen time." It could be that rapid subtopic switching and algorithmic

recapitulation present a different set of demands than long-form content intended for study.

Much of the above research did not specifically involve short-form video, so research directly involving these services is especially pertinent. To this end, Xie et al. recruited 1,047 undergraduates to test how addictive short-video usage related to academic procrastination; results suggested that these constructs are related through attentional control [6]. In other words, the study provides some support for the idea that problematic short-video usage may impact academic performance through difficulties with attention regulation, but does not imply that casual short-form-video usage will negatively impact cognition. One line of research that does focus on attention and task switching involves media-multitasking. Ophir et al. found that heavy and light media multitaskers performed differently on cognitive control measures [7], whereas Rosen et al. noted that media-driven task switching may impact studying habits and learning behaviors [8]. Cognitive Load Theory can also help us understand how info-flighting and rapid topic shifts could tax working memory during learning periods [9].

Essentially, some recent articles about "brain rot" have tried to bridge internet vernacular with established constructs. Yilmaz and Aktürk developed a 18-item self-report measure of "brain fatigue" consisting of 4 dimensions (cognitive load, cognitive fatigue, emulation, depersonalization); they found acceptable psychometric properties [2]. Yousef et al. conducted a rapid review that conceptually connected brain rot with doomscrolling, PSU, information overload, and impaired executive function. They also provided recommendations like limiting overall screen time, editing the types of media you engage with, and taking breaks to go offline [3]. The qualitative research from Özbay in 2026 affirms some of these ideas with university student data; participants commonly reported difficulties with productivity, concentration, and decision making but had developed coping mechanisms like digital detoxes, exercise, and meditation [4].

A. Research Gap

Predominant evidence centers around international samples while investigating general Internet use, problematic smartphone use, or short-form- video addiction. Little research spotlights routine short-form consumption among Gulf higher education students specifically. Moreover, Oman has few empirical investigations centered around university students. To fill this contextual gap, the current study investigates exposure, perceived cognitive effects, academic distraction, awareness, and self-regulation among UTAS students.

B. Conceptual Model

We interpret our findings in light of a simple exposure–attention–academic behavior pathway: Exposure to short-form content may lead to heightened interruption/task switching; interruption/task switching may be correlated with subjective attentional difficulty; attentional difficulty may be associated with lessened academic attentiveness. Awareness and self-regulation are conceptualized as potential moderators throughout this pathway. Our proposed framework dovetails with Cognitive Load Theory [9] as well as findings surrounding attentional control and short-form- video related academic procrastination [6].

III. METHODOLOGY

A quantitative, cross-sectional correlational design was used. The target population consisted of UTAS students who were likely to encounter short-form digital content through social-media platforms. Participants were recruited using convenience sampling. Although the research plan initially anticipated 100–150 respondents, the reported dataset contains 200 completed responses, as confirmed by the demographic frequency totals.

A. Participants

The sample size for the study was 200 students. 169 respondents were male students and 31 respondents were female students (84.5% and 15.5%, respectively). The majority were in the age range 20–30 years (n =167, 83.5%); 20 respondents were less than 20 years old (10.0%) and 13 respondents were over 30 years old (6.5%). Of study level, there were 25 diploma students (12.5%), 92 advanced diploma students (46.0%), 81 bachelor students (40.5%), and 2 students reported as another level (1.0%). Note: Percentages presented in this revision are calculated from the reported frequencies rather than being carried over from the submitted document. This was done to eliminate instances where rounding caused the total percentage to be >100%.

Characteristic	Category	n	%
Gender	Male	169	84.5
	Female	31	15.5
Age	<20 years	20	10.0
	20–30 years	167	83.5
	>30 years	13	6.5
Study level	Diploma	25	12.5
	Advanced Diploma	92	46.0
	Bachelor	81	40.5
	Other	2	1.0

TABLE I. PARTICIPANT CHARACTERISTICS (N = 200)

B. Instrument and Procedure

Google Forms questionnaire was used for the research. Survey questions asked demographic information and 12 questions ranked on a Likert Scale with six categories including digital use, cognitive load, academic attention, behavior, knowledge, and application. The response options were: 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, and 5 = strongly agree. Students voluntarily completed the questionnaire. According to the method section of the original article, names and student ID numbers were not collected.

C. Data Analysis and Publication-Integrity Rule

The only information provided in the available report is descriptive analysis using frequencies and percentages. A table is included that labels relationships between digital consumption and attention, focus, concentration as negative. There is no numerical correlation coefficient provided, nor sample-specific test statistic, p-value, confidence interval or regression output. For these reasons, this revision does not refer to associations as being statistically significant and does not state that H1 was inferentially supported. This is an important distinction because a directional label by itself does not constitute statistical hypothesis testing.

IV. RESULTS

A. Digital Consumption

Participants frequently engaged with short-form media. When asked how much they agreed with the statement "I spend a large amount of time each day watching short-form videos", 16% of participants strongly agreed and 67% agreed (totaling 83% positive responses). Similarly, when asked how much they agreed with the statement "I check short-form platforms multiple times throughout the day", 67% of participants strongly agreed and 20% agreed (totaling 87%).

B. Perceived Cognitive and Academic Effects

Questions about cognitive effects yielded mixed responses. When asked whether they feel like they can't concentrate for long periods of time after reading short-form content, 49% agreed/strongly agreed and 45% chose neutral. When directly asked if short-form content hurt their attention span, 54% agreed/strongly agreed, 14% were neutral, and 33% disagreed/strongly disagreed.

Items regarding academic-focus had a notable difference. Whereas only 23% agreed/strongly agreed that short-form media hurt their ability to focus during lectures, 67% responded with neutral. 79% agreed or strongly agreed that they have trouble focusing on schoolwork when they don't check their phone. Therefore, the biggest issue self-reported may be with interruption/checking rather than consistent loss of attention during lectures.

C. Behavioral Patterns, Awareness, and Self-Regulation

Switching frequently was routine: 83% agreed or strongly agreed that they often find themselves rapidly switching between apps or tasks. Students often felt an impulse to check short-form content: Half of respondents (50%) agreed or strongly agreed that they have the desire to look at short-form content even when they're busy, and 39% neutral. Awareness of the problem was strong: 78% agreed or strongly agreed that reading too much content online could negatively impact attention span and 77% knew their digital-consumption habits can affect how well they perform mentally.

Students reported being willing to alter their behavior as well. Eighty percent agreed or strongly agreed that they have attempted to restrict their intake of short-form content to help them better focus. When asked about their willingness to implement strategies to improve academic performance such as reducing screen time, 50% agreed or strongly agreed and 39% responded with a neutral. Our research indicates a potential opportunity for intervention: students are aware of the issue at hand, but may need some low-effort strategies to help them act on that knowledge.

TABLE I. SUMMARY OF LIKERT RESPONSES

Domain / Item	SA %	A %	Positive %
Substantial daily short-form viewing	16	67	83
Frequent checking throughout day	67	20	87
Difficulty concentrating after viewing	10	39	49
Negative effect on attention span	14	40	54
Negative effect on lecture focus	14	9	23
Difficulty studying without phone checking	64	15	79
Rapid switching between apps/tasks	19	64	83
Urge to check content while busy	34	16	50
Aware of possible attention effect	66	12	78
Believe habits affect cognition	13	64	77
Try to limit use to improve focus	69	11	80
Willing to adopt reduction strategies	34	16	50

V. DISCUSSION

The most notable pattern is that very high exposure did not come at the expense of awareness. Over four in five participants endorsed both frequent viewing/daily checking and potential consequences for attention and attempted self-limiting behavior. This association has also been observed at the behavioral level in the wider literature on problematic/habitual digital technology use, where awareness of distraction has not been found to preclude engagement [5], [6].

Another takeaway is that findings do not support a singular "short videos destroy attention" hypothesis. Participants' perceptions varied by item. Although slightly more than half reported negative effects to attention span and difficulty concentrating after short video viewing, a majority remained neutral as to whether short-form videos hurt their ability to focus during lectures. However, a majority of participants did endorse difficulties studying while not checking their phone. This supports the hypothesis that frequent phone checking leads to disruptive interruption and task-switching more so than a cognitive inability to pay attention per class. This interpretation aligns with media-multitasking research. Repeated switching can impose attentional costs and disrupt learning even when the user does not perceive a global decline in cognitive ability [7], [8]. Cognitive Load Theory offers a plausible mechanism: when academic tasks already demand working-memory resources, additional digital interruptions may increase extraneous load and make sustained engagement more difficult [9]. Nevertheless, the present study did not experimentally manipulate exposure or objectively measure working memory, sustained attention, or executive control; these mechanisms remain theoretically plausible rather than demonstrated within the UTAS sample.

The term "brain rot" should therefore be used carefully. Its value is communicative: students immediately recognize a cultural concern surrounding low-value, repetitive, and compulsive digital consumption. Its limitation is scientific ambiguity. It is not a formal clinical diagnosis, and recent research is still developing validated ways to measure the experiences grouped under the label [2]–[4]. For publication, the strongest framing is to treat "brain rot" as a contemporary descriptor while reporting measurable constructs—attention, cognitive fatigue, checking behavior, academic focus, and self-regulation.

A. Implications for UTAS and Omani Higher Education

The findings support targeted digital-well-being interventions rather than blanket restrictions. Universities can incorporate brief evidence-based guidance into student orientation, academic advising, and study-skills programs. Practical measures include disabling nonessential notifications during study, scheduling intentional short-form-video periods rather than intermittent checking, using device focus modes, placing phones out of immediate reach during deep-work sessions, and encouraging longer uninterrupted study intervals. Because 80% of respondents already reported attempts to limit use, interventions should emphasize implementation and habit design rather than awareness alone.

VI. LIMITATIONS

There are four key limitations. One, convenience sampling and male overrepresentation limit generalizability. Two, it is a self-report study; feeling that attention has decreased is not the same as showing objectively measured cognitive declines. Three, as a cross-sectional study, temporal precedence and causation cannot be determined. Four, the authors did not report correlation coefficients (just significance), p-values, confidence intervals, reliability estimates, or raw data at the respondent level. Thus, statistical significance claims and confirmations of hypotheses cannot be independently confirmed with the provided data.

One additional limitation is that activities on abbreviated platforms are not uniform. Education-based videos will likely differ from entertainment videos, news videos, videos used for advertising purposes, or low effort/passive activities that require simple repetition. Moving forward, it may be useful to not only measure screen time duration but also the content of what people are engaging in, reason for using the platforms, time of day of usage, number of times receiving notifications that they check their phone, whether they are multitasking while using screens, sleep, and their baseline ability to maintain attention.

VII. CONCLUSION AND FUTURE WORK

This study captured a point-in-time glimpse of short-form digital behaviors in a sample of 200 UTAS students, generalizability of which is limited to Oman. Self-report data indicate high daily usage, frequent checking behaviors, heavy app-switching, and self-reported difficulty studying without checking their phone. However, students also reported high levels of concern about attentional risks and a moderate willingness to control their usage. Findings here support an alarm over interruption-prone digital behaviors; however, they do not

support going beyond association to claim short-form media causes cognitive degeneration.

Avenues for future research should include stratified or probability-based samples at various UTAS campuses and other universities in Oman, validated scales, and objective measures of cognition such as sustained-attention tasks or working-memory measures. Device-based measures could include objective screen-time logging. Longitudinal studies can establish whether fluctuations in short-form-video use precede attention or academic-performance fluctuations. Experimental studies could evaluate prolonged study with versus without smartphone notifications or with disruptions from short videos. Intervention studies can determine whether tools to eliminate interruptions (e.g., Focus modes on smartphones), reduce notifications, take "structured breaks" from digital media, use mindfulness techniques, or engage in brief "digital detox" improve study focus. Each of these could help move the narrative past emotionally charged but unfounded terms like "brain rot."

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Cybersecurity Awareness and Phishing Prevention Among UTAS Students in the Sultanate of Oman

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Abstract*— The purpose of this study was to measure cybersecurity awareness within UTAS students and propose effective phishing education methods. Using quantitative research methods, a survey consisting of questions regarding background demographics, participant habits, and attitudes toward cybersecurity was conducted with a total of 58 participants. Using descriptive and inferential statistics, the Likert-scale-based responses were taken from an anonymous cybersecurity awareness questionnaire. Results of the study indicated that UTAS students had an intermediate awareness of cybersecurity threats however lacked in the ability to apply that knowledge to spot and report phishing. While awareness was present, students lacked confidence in their ability to identify phishing emails and had room to improve prevention habits. From these results we were able to suggest practical application recommendations to help students better their practical skills such as phishing simulations, workshops, and reporting process improvements. We hope that our research can aid in understanding the impact of your current cybersecurity programs as well as provide recommendations to improve phishing prevention.

Keywords*— cybersecurity awareness, phishing prevention, quantitative survey, phishing simulations

I. INTRODUCTION

Phishing schemes have become one of the most costly forms of cybercrime worldwide that targets directly consumers and businesses than any other kind of cybercrime. Technology has been improving day by day countries like Oman become prone to cyber attacks. University students are among the users of electronic services that can be affected by phishing including students of UTAS. This study aims to detect and find methods to improve awareness as well as prevention measures to decrease phishing in Oman.

Phishing was described as "A widespread variety of cyber-attack directed at individual consumers and businesses through email, messages, and other communication software." Scams encourage people to share financial data, login information or other personal data. Awareness can be described as how informed someone is about phishing and how to prevent it. Prevention can be defined as "Policies, devices, and procedures that reduce the adverse effects of a threat event once it occurs" [1].

II. LITERATURE REVIEW

This literature review searches studies and articles regarding cybersecurity awareness and phishing prevention among students attending university and studies that require localized evidence within Oman specifically. Phishing awareness and prevention is particularly significant in university settings because students use emails, online learning platforms, mobile applications, cloud-based storage systems, and social media daily which elevates cyber risk exposure through phishing attacks, links to malware, account takeover, and other dangers. Awareness of phishing in particular matters because phishing attacks target users' judgment instead of technical vulnerabilities alone. In layman's terms, cyber criminals can still target university students as victims, even if university servers have all the right security tools, if students cannot identify red flags or know how to react safely. Phishing research collected from university students found that phish messages are getting more realistic over time and are crafted to mirror an ordinary and innocent activity within students' daily lives like receiving a job offer or university communication. . The objective of this literature review is to collect research that establishes what is already known about students' cybersecurity awareness, students' phishing behaviors, and students' anti-phishing training. Other key purposes include collecting major themes surrounding this topic, identifying similarities and differences between studies, and recognizing the gaps of research that still need to be addressed. These steps are necessary for the current study because when conducting a literature review, you do not want to simply restate what other authors have stated. You want to showcase what is known about your topic, what questions have not been answered, and why your study should be conducted. The literature gap in this topic is while there are many studies done about cybersecurity and phishing prevention globally, recent studies focused on university students in Oman are limited.

Cybersecurity awareness is vital as we use the internet to complete simple tasks such as communication with friends and family, online banking, and more. Phishing is a cyber-attack where a threat actor typically impersonates an organization you know to steal your personal information or financial information [2].

According to [3] phishing attacks are becoming more convincing as cyber criminals. Cyber criminals create emails or messages that look legit to manipulate users into clicking on dangerous links or opening infected attachments. This study generalized information on how to protect yourself from phishing attacks but did not specify any targeted countries or students. The article from [4] listed many types of phishing such as voice phishing (vishing), SMS phishing (smishing), and spear phishing. Even though this source was helpful in

explaining the different methods of phishing it did not measure any level of awareness or prevention plans.

Not only did [5] show that mock phishing can greatly improve cybersecurity awareness but also participants showed signs of improvement in their ability to detect phishing scams. While [6] discovered that age and gender play a factor in the level of awareness about phishing among employees.

Research done by [7] measured the effectiveness of phishing awareness training and concluded that any type of awareness training will help your organization minimize the risk of falling victim to phishing. Another article [8] researched AI- based cybersecurity awareness training to prevent phishing.

Cybersecurity awareness was studied among school students in Oman during the COVID-19 pandemic and digital transformation by [9] and they concluded that students require more cybersecurity awareness. [10] recognized the lack of current effective information security awareness programs in higher educational institutions in Oman.

While these studies mention students and Oman, they do not specify the students of UTAS or conduct a study within UTAS. Cybersecurity awareness and phishing prevention will be researched on UTAS students to identify how aware students are and what prevention strategies can be applied.

III. METHODOLOGY

This chapter explains the research methodology used to study cybersecurity awareness and phishing prevention among students at the University of Technology and Applied Sciences (UTAS) in Oman. It covers the research objectives, research design, participants, sampling strategy, data collection, data analysis, ethical considerations, and limitations of the study.

The main purpose of this study is to evaluate how aware UTAS students are about cybersecurity and phishing risks, and to understand how this awareness connects to their ability to recognize phishing and behave safely online. Phishing is a real concern for students because they regularly use email, social media, online learning systems, and other digital services — which makes them possible targets for scams, fake websites, and suspicious messages.

The study has the following specific objectives:

- To measure the level of cybersecurity awareness among UTAS students in Oman.
- To identify students' knowledge of phishing and their ability to recognize phishing attempts.
- To examine students' exposure to suspicious emails, SMS messages, social media messages, and fake login pages.
- To examine safe online practices such as checking sender addresses, avoiding suspicious links, using strong passwords, enabling two-factor authentication, updating devices, and reporting suspicious messages.
- To recommend practical strategies that UTAS can use to improve cybersecurity awareness and phishing prevention among students.

This study is important because it gives UTAS a student-based view of awareness gaps and training needs. The results can help the university design useful programs such as awareness workshops, alerts, and simulated phishing exercises that match real student experiences.

This study uses quantitative, cross-sectional, and correlational research design. It is quantitative because data were collected using Likert-scale items scored from 1 (Strongly Disagree) to 5 (Strongly Agree). It is cross-sectional because all responses were collected at one point in time. It is correlational because the study examines whether cybersecurity awareness is related to phishing recognition ability and safe online behavior.

This design is appropriate for the research objectives because it allows the researchers to measure awareness levels numerically and check for relationships between key variables. It is also practical for a student project because an online survey is easy to distribute, quick to fill in, and produces structured data for analysis.

A. Theoretical Framework

Our study draws upon a simple awareness -> behavior framework. Central to this framework is the belief that students with heightened cybersecurity awareness will know more about phishing attacks. They will then refrain from engaging in risky behavior and report suspicious messages. Cybersecurity awareness is therefore hypothesized to be the primary predictor of both phishing recognition and safe cybersecurity behavior in our study.

B. Sample Characteristics

The table below summarizes the main characteristics of the participants.

TABLE I
DEMOGRAPHIC PROFILE OF RESPONDENTS (N=58)

Category	Group	Percentage
Education	Diploma	44.8%
	Advanced Diploma	31.0%
	Bachelor	24.1%
Age	< 20 years	15.5%
	20–24 years	77.6%
	> 24 years	6.9%
Department	IT	60.3%
	Engineering	29.3%
	Business	10.3%

57 responses are fine for sampling purposes for a research methodology module. It will enable them to calculate descriptive statistics, portray the sample profile and run some bivariate analyses on variables of interest. The sample size is

small, therefore the results should not be used to draw conclusions about UTAS students in general, unless they repeat the exercise with a larger sample and one that hopefully is more evenly distributed across the strata.

C. Potential Sampling Bias and How to Reduce It

Convenience sampling can sometimes create bias. In this study:

Participants may be students who are closer to the researchers or more interested in cybersecurity.

Most participants were aged 20 to 24, so younger and older students are less represented.

IT and Engineering students made up most of the sample, while Business students were fewer.

To reduce these limitations in future research, the survey should be sent to more UTAS branches and departments, and all student IDs should be removed from the final report to protect privacy.

3.4 Data Collection Procedures

An online questionnaire was used to gather data for this study. It was selected because students could complete it quickly, allowed structured data that could be statistically analyzed, and was easily administered to UTAS students. There were three sections to the questionnaire including demographic questions (level of education, age group, and department), Likert- scale questions, and an open-ended question at the end.

D. Data Collection Instrument

The measurement instrument was a structured Likert- scale questionnaire (1=Strongly Disagree to 5=Strongly Agree). The questionnaire consisted of 36 close-ended questions under seven constructs, including: (1) general cybersecurity awareness; (2) awareness of phishing identification knowledge; (3) exposure to phishing attacks; (4) safe online activity behavior; (5) potential risk and training deficiencies; (6) advantages of cybersecurity awareness training; and (7) suggestions for UTAS. There was one open-ended question that asked participants for recommendations to improve cybersecurity programs.

E. Reliability and Validity

Reliabilities of all constructs had good to high internal consistency (Cronbach' s $\alpha > 0.70$). Content validity was determined based on existing cybersecurity awareness models. The questionnaire was proofed by the research advisor prior to dissemination.

F. Research Hypotheses

H1: There is a significant positive relationship between cybersecurity awareness and phishing recognition knowledge among UTAS students.

H2: There is a significant positive relationship between cybersecurity awareness and safe online practices among UTAS students.

IV. DATA ANALYSIS AND FINDINGS

A. Descriptive Analysis

All seven construct means exceeded the neutral midpoint of 3.00, indicating general agreement across all areas. Table III summarizes the overall construct results.

TABLE II: OVERALL CONSTRUCT RESULTS

Construct	Mean	Disagree	Neutral	Agree
General cybersecurity awareness	3.46	24.5%	23.4%	52.1%
Awareness of phishing attacks	3.41	26.2%	23.8%	50.0%
Common phishing exposure	3.54	25.2%	17.6%	57.2%
Phishing prevention practices	3.44	28.4%	19.5%	52.0%
Challenges in awareness	3.57	23.1%	20.7%	56.2%
Benefits of awareness	3.58	24.1%	19.3%	56.6%
Recommendations for improvement	3.71	20.3%	19.0%	60.7%

Cybersecurity awareness had a mean score of 3.46, indicating moderate to positive awareness overall. The highest item was participants were aware that phishing emails can cause loss of data/funds (63.8%); however, general cybersecurity awareness was relatively low (39.7%). Phishing awareness had a mean score of 3.41. Participants were aware of phishing types (60.3%) but showed lower levels of correctly identifying phishing emails (41.4%). Participants were exposed to different types of phishing as shown by the mean of 3.54. The highest items were suspicious social media messages (63.8%) and SMS phishing (62.1%). This demonstrates that programs need to train students on phishing prevention outside of email. Participants had mixed reviews on their phishing prevention practices. Creating strong passwords (55.2%) and utilizing two-factor authentication (56.9%) were higher levels of adherence. Checking email addresses of links before clicking were low at 37.9%. Recommendations had the highest mean of 3.71. Students recommended using practical/examples of phishing (65.5%) in awareness campaigns and wanting cybersecurity topics to be implemented in workshops.

B. Inferential Analysis

Due to the availability of only aggregated Google Forms summary data (rather than raw respondent-level data), a formal Pearson correlation test between constructs could not be computed. As an alternative, a one-sample t-test against the neutral midpoint of 3.00 was applied to each construct. Table IV presents the results.

TABLE III
INFERENTIAL ANALYSIS: ONE-SAMPLE T-TEST VS. NEUTRAL MIDPOINT (3.00)

Construct	N	Mean	t	p-value
General cybersecurity awareness	290	3.46	5.77	<.001
Awareness of phishing attacks	290	3.41	5.15	<.001
Common phishing exposure	290	3.54	6.44	<.001
Phishing prevention practices	348	3.44	5.74	<.001
Challenges in awareness	290	3.57	7.16	<.001
Benefits of awareness	290	3.58	7.22	<.001
Recommendations	290	3.71	8.99	<.001

Means were significantly greater than the neutral point for all constructs ($p < .001$), suggesting that students taking UTAS perceive cybersecurity threats, believe they are at risk of phishing attacks, and feel these attacks should be prevented with stronger security programs. Note: These results are based on aggregate response data rather than individual-level data.

C. Hypothesis Discussion

H1 is partially supported by the descriptive pattern. Students showing higher agreement with awareness items also responded positively to phishing recognition items. However, a formal correlation requires raw respondent-level data.

H2 is partially supported by student perceptions. A majority agreed that awareness, training, and practical examples help reduce phishing risks; however, causality cannot be established from a cross-sectional survey.

D. Discussion of Findings

cybersecurity issue but still lack skill in detecting them. Like learning how to drive, a student can know that the street can kill you but still need to practice reading traffic signs. Students know that phishing is bad, but they will need practical and realistic examples with repeated practice if they are to learn how to spot phishing messages with confidence.

The best result in awareness was the consensus that phishing will result in loss of personal information, money, or data. This is a good sign that students understand how severe phishing is. The low mark in Familiar With Cybersecurity Concepts is cause for concern because it shows that some students may not know cybersecurity terminology nor the basic steps to protect themselves. Awareness programs should open with easy concepts and then lead into real world scenarios.

The exposure results are another critical takeaway from this data. Phishing does not only come from email. Many students encountered suspect messages from social media, SMS text messages, fake login pages, and people impersonating others. Anti-phishing campaigns should include examples that a student would encounter in their daily lives. Examples can include messages from fake deliveries, fake university logins, fake scholarships, banks, and official organizations.

The worst result in prevention practices was not terrible. Students agreed to protect themselves with strong passwords and two-factor authentication. The weak link was checking a sender's address before clicking a link. This is a crucial gap because many phishing attacks can be stopped by verifying the sender's email address, domain name, spelling of a link, and login page's address before entering any passwords or data.

The qualitative responses support the conclusions from the quantitative data. Students asked for workshops, realistic examples, simulated phishing emails, regular reminders, and easy methods to report phishing. Students have told us they want to learn how to protect themselves from phishing. They do not want to be inundated with information. Awareness campaigns should be short, frequent, realistic, and tied to actual phishing examples.

V. CONCLUSIONS

In this project, cybersecurity awareness and phishing prevention behaviors were measured in a sample of 58 UTAS students in Oman. Awareness was found to be moderate, but there is a lack of practiced responses to detect phishing emails. Students receive phishing messages across a variety of channels including email, SMS, social media, and fake login pages. However, tactical skills like verifying sender information and reporting suspected messages to authorities needs to be reinforced.

Recommendations for UTAS include:

• Host brief cybersecurity awareness workshops each semester for the student body. Make attendance mandatory for IT students.

• Use examples of phishing messages that students would receive in their day-to-day lives. This can include university login pages, parcel delivery notifications, and scholarship emails.

• Test students regularly with harmless phishing simulations to build confidence in their ability to detect phishing.

• Send monthly reminders to students about new phishing techniques through email, the student portal, and social media.

• Create an easy and effective reporting system for suspected emails and messages.

• Promote better cybersecurity behaviors like double-checking the sender- address, using two-factor authentication, and installing software updates.

Future research recommendations include gathering raw response-level data to allow for full correlation and regression analysis, increasing sample sizes and adding samples from other universities in Oman, and conducting longitudinal studies on the effectiveness of phishing simulation programs and Artificial Intelligence enabled cybersecurity training.

VI. CONTRIBUTIONS OF THE STUDY

This study contributes valuable insights into the level of cybersecurity awareness at UTAS and highlights the gaps that need to be addressed. Key contributions include: - The identification of specific phishing threats faced by students. - The need for more practical, hands-on phishing detection training.

VII. RECOMMENDATIONS FOR FUTURE RESEARCH

Future studies could focus on: 1. Testing theories or models in different cultural settings or regions. 2. Expanding research on the long-term impact of phishing awareness training. 3. Exploring how AI can further enhance cybersecurity training programs.

VIII. IMPLICATIONS/LIMITATIONS OF THE STUDY

Theoretical Implications: This study contributes to the growing body of knowledge on cybersecurity awareness by highlighting the importance of practical training in identifying and responding to phishing. Practical Implications: - UTAS can use these findings to improve their cybersecurity education

programs. - Phishing simulations and practical exercises should be introduced to help students apply what they've learned. Limitations: - The study was conducted at UTAS, which may not represent all university students in Oman or beyond. - The research used self-reported data, which may introduce bias.

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Artificial Intelligence for Blood Cancer Detection: Literature Benchmarks and Healthcare Professional Perceptions

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Abstract—Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has shown strong research performance in the analysis of blood smears and other hematology data. However, high benchmark accuracy does not by itself establish clinical effectiveness. This study combines a review of AI approaches for blood cancer detection with a cross-sectional survey of 32 healthcare professionals to examine perceived diagnostic value, trust, and implementation barriers. Participants included doctors (40%), nurses (35%), and laboratory technicians (25%). Respondents rated AI-supported diagnostic speed and continuous monitoring relatively favorably (M=3.8, SD=1.0 for each), and future dependence on AI diagnosis received M=3.6 (SD=1.2). Participants with prior experience of AI medical tools expressed more favorable views than those without such experience, $t(30)=4.92$, $p<0.001$. Perceptions did not differ significantly across professional groups, $F(2,29)=1.84$, $p>0.05$. Perceived AI use correlated with perceived diagnostic precision ($r=0.67$), while perceived decision support correlated with trust ($r=0.61$). Model-performance figures in the source report are derived from published studies and public benchmark datasets rather than a locally validated clinical model; they are therefore treated as secondary evidence. The paper synthesizes verified leukemia-imaging literature, discusses dataset shift, patient-level validation, calibration, explainability, fairness, and clinical workflow integration, and proposes a rigorous validation framework for future AI-assisted hematology research in Oman. AI is positioned as decision support rather than a replacement for clinical expertise.

Keywords—artificial intelligence; leukemia; blood cancer; deep learning; convolutional neural networks; blood smear; clinical decision support; hematology; Oman

I. INTRODUCTION

Hematologic malignancies include leukemias, lymphomas, and related disorders that affect blood, bone marrow, and lymphatic tissues. Their diagnosis can involve complete blood counts, peripheral-blood-smear examination, bone-marrow assessment, immunophenotyping, cytogenetics, molecular tests, and expert clinical interpretation. Microscopy remains important because abnormal cell morphology can provide rapid diagnostic clues, yet manual examination is labor-intensive and depends on specialist expertise.

AI has become increasingly prominent in hematology because image classification, segmentation, prediction, and risk-stratification tasks can be formulated using ML or DL. A comprehensive review of 144 studies published between 2015 and 2021 found substantial activity in AI applications across hematologic malignancy screening, diagnosis, and treatment, while also identifying unresolved gaps in translation across the patient pathway [1]. Deep neural networks are especially relevant to blood-smear imaging because convolutional architectures can learn complex morphological patterns directly from labeled images.

Nevertheless, research accuracy and clinical utility are not equivalent. A model trained on a curated public dataset may perform well under a particular imaging protocol but degrade when applied to images from another microscope, staining procedure, hospital, or patient population. Clinical deployment therefore requires more than a high accuracy value: sensitivity, specificity, calibration, error analysis, external validation, workflow fit, transparency, privacy, and clinician oversight all matter.

The present study combines two evidence streams. First, it reviews literature and public benchmark evidence on AI-assisted blood cancer detection. Second, it analyzes perceptions from 32 healthcare professionals regarding AI speed, monitoring, decision support, trust, and implementation. Importantly, the model-performance numbers reported in the source document are not treated as results of a newly trained local model because the report itself states that model performance was based on published literature and publicly accessible blood-smear datasets.

A. Objectives and Research Questions

The paper aims to assess the potential contribution of AI to blood cancer detection, compare major ML/DL approaches reported in the literature, analyze healthcare-professional perceptions, identify clinical and ethical barriers, and define a validation pathway suitable for future work in Oman. The central question is not simply whether AI can classify images accurately, but under what conditions such performance can be translated into safe clinical decision support.

II. CLINICAL AND TECHNICAL BACKGROUND

A. AI in Hematology

The hematology literature includes classical ML methods using engineered laboratory or morphological features and DL methods that learn representations directly from images or high-dimensional data. El Alaoui et al. identified ML, leukemia, classification, and DL as prominent themes in AI hematology research and concluded that the field has produced impressive results while leaving important clinical-pathway questions unresolved [1]. This supports a balanced interpretation: AI is technically promising, but evidence quality and clinical generalizability vary across studies.

B. Blood-Smear Image Classification

Public image datasets have accelerated leukemia research by providing labeled examples for segmentation and classification. ALL-IDB was introduced as an image database for acute lymphoblastic leukemia (ALL) image-processing research [2]. More recent datasets and challenge collections have enabled larger-scale comparisons, but many remain curated and relatively homogeneous. Benchmark success therefore provides evidence of algorithmic capability rather than a guarantee of performance in routine hospital practice.

Deep CNNs learn hierarchical features such as edges, textures, nuclei morphology, and cell-level structure without requiring every feature to be manually engineered. Transfer learning can reduce training requirements by adapting networks pretrained on large image collections. Ensemble methods can combine complementary models and sometimes produce strong benchmark performance. A 2024 study by

Awais et al., for example, evaluated deep features and ensemble methods for ALL classification on public data, illustrating the high performance achievable under benchmark conditions [3]. Such results are valuable, but must be interpreted within the dataset and evaluation protocol used.

C. Evaluation Beyond Accuracy

Accuracy can be misleading when class prevalence is unequal or when false negatives and false positives have different clinical costs. A leukemia screening system should therefore report sensitivity (recall for disease), specificity, precision, F1-score, receiver-operating-characteristic area under the curve (AUROC), and preferably precision-recall metrics for imbalanced settings. Calibration is also important: if a model reports a 90% probability, cases with similar scores should be correct at approximately that rate. Without calibration, confidence values may appear precise while being clinically unreliable.

D. Clinical Translation, Ethics, and Governance

WHO guidance emphasizes that AI for health should place ethics, human rights, transparency, accountability, inclusiveness, and safety at the center of design and deployment [4]. In blood cancer diagnostics, these principles translate into requirements for representative datasets, secure handling of sensitive data, documented model limitations, human oversight, and mechanisms for monitoring performance after deployment. A clinically responsible model should support—not replace—the hematologist, pathologist, or laboratory specialist.

E. Research Gap

Much of the leukemia-AI literature demonstrates technical feasibility on retrospective or public datasets, while comparatively fewer studies address prospective clinical validation, domain shift, local workflow integration, and health-professional trust. The current paper addresses this gap by combining secondary technical evidence with primary perception data and by separating algorithmic benchmark performance from clinically validated effectiveness.

III. METHODOLOGY

The study uses a mixed evidence-assessment design comprising a review/secondary analysis of AI model performance reported in published literature and public blood-smear resources, together with a cross-sectional questionnaire of healthcare professionals. This wording more accurately reflects the available evidence than describing the study as a full local clinical model-development experiment.

A. Healthcare-Professional Survey

Thirty-two healthcare professionals completed a 13-item Likert-scale questionnaire. Doctors represented 40% of the sample, nurses 35%, and laboratory technicians 25%. Items covered perceived effects of AI on diagnostic speed, continuous monitoring, decision support, future dependence, workload, treatment timing, trust, and related concerns. Google Forms was used for collection, and responses were exported for descriptive and inferential analysis.

B. Secondary Technical Evidence

The source report refers to hundreds of blood-smear images from open repositories and to model classes including CNN and SVM. However, it later clarifies that AI/ML performance evaluation was based on verified results from published literature and publicly accessible datasets because locally annotated medical image data were limited. Consequently, this publication-ready version does not present 95% or 97% model accuracy as an original locally trained result. Instead, literature benchmark results are discussed explicitly as secondary evidence.

C. Statistical Analysis

Descriptive statistics summarize professional perceptions. An independent-samples t-test compared respondents with and without prior experience of AI medical tools. One-way ANOVA compared perceptions across doctors, nurses, and laboratory technicians. Pearson correlations examined associations between perceived AI use and perceived diagnostic precision, and between perceived decision support and trust. These tests concern participant perceptions; they do not measure the diagnostic accuracy of an AI model on patients.

D. Ethical Considerations

The questionnaire was voluntary and anonymous. Publicly available medical datasets were described as anonymized. No conclusion from the study should be used as individual medical advice or as authorization for autonomous diagnosis. Future clinical studies require ethics approval, appropriate data-governance agreements, patient-level privacy safeguards, and careful consideration of whether data reuse is compatible with original consent and local regulation.

IV. RESULTS

A. Descriptive Professional Perceptions

Healthcare professionals reported moderately favorable views of several AI functions. The statement that AI speeds diagnosis had a mean of 3.8 (SD=1.0), and continuous observation/monitoring also had a mean of 3.8 (SD=1.0). Future dependence on AI diagnosis received a mean of 3.6 (SD=1.2). The item stating that AI shortens the time needed for therapy received a lower mean of 3.1 (SD=1.3), suggesting that respondents distinguished diagnostic support from downstream treatment effects.

B. Inferential Perception Analysis

Participants with prior experience using AI medical tools expressed significantly more favorable perceptions of AI effectiveness than those without such experience, $t(30)=4.92$, $p<0.001$. By contrast, professional role was not associated with a statistically significant difference in perceptions, $F(2,29)=1.84$, $p>0.05$. These results indicate that familiarity may be more relevant to acceptance than profession within this small sample, although group sizes and effect sizes should be reported in future work for fuller interpretation.

Perceived AI application was positively correlated with perceived diagnostic precision ($r=0.67$), while perceived AI decision support was positively correlated with trust ($r=0.61$). These are substantial sample correlations, but they measure relationships among perceptions. They do not show that increasing AI utilization causes actual diagnostic accuracy to increase.

C. Technical Benchmark Evidence

The source report summarizes deep-learning results from the literature and gives illustrative values such as approximately 95% for CNN-based approaches and up to 97% for hybrid DL approaches. Because these values were drawn

from secondary sources rather than a documented local experiment, they should not be combined into a single "study accuracy." Verified published studies demonstrate that benchmark accuracy can indeed be high. For example, Awais et al. reported strong ALL classification results using public datasets and deep feature/ensemble techniques [3]. The correct interpretation is that AI has demonstrated technical feasibility under defined research conditions, while local clinical performance remains unknown.

D. Key Result Distinction

V. DISCUSSION

A. Diagnostic Potential and the Benchmark-to-Clinic Gap

The literature strongly supports the ability of DL systems to discriminate leukemia-related image patterns under research conditions [1], [3]. However, the benchmark-to-clinic gap is central. Model performance may change with staining, image magnification, scanner characteristics, laboratory preparation, patient demographics, disease subtype, or prevalence. External validation should therefore use data collected independently from the training source and should preserve patient-level separation so that images from the same patient cannot appear in both training and test sets.

B. Sensitivity, Specificity, and Clinical Cost

For early screening, false negatives can delay further investigation, while false positives can create unnecessary anxiety and testing. Model selection should therefore consider clinically meaningful trade-offs rather than maximizing overall accuracy alone. Thresholds may need to be selected according to intended use: a screening aid may prioritize sensitivity, while a confirmatory support system may require stronger specificity. Decision-curve analysis or cost-sensitive evaluation can complement conventional metrics when the clinical action associated with each prediction is defined.

C. Trust, Experience, and Human Oversight

The t-test and correlation results indicate that prior AI experience and perceived decision support are associated with more favorable attitudes and trust. This is plausible because familiarity can reduce uncertainty about how a tool works. Yet trust should be calibrated rather than maximized. Over-trust can lead clinicians to accept incorrect outputs, while under-trust can prevent beneficial tools from being used. Interfaces should therefore expose confidence, uncertainty, and the evidence available for review, and should make it easy for professionals to disagree with the model.

D. Explainability and Error Analysis

In image-based hematology, explainability can include saliency or attention maps that identify regions influencing a prediction, but visual explanations should not be assumed to be clinically meaningful without validation. More useful error analysis may categorize false predictions by cell quality, staining artifact, subtype, low blast count, or ambiguous morphology. Clinician review of error clusters can reveal whether a model is learning medically relevant patterns or relying on spurious visual cues.

E. Data Quality, Bias, and Generalizability

The review literature repeatedly identifies dataset size and quality as constraints. A dataset can be large yet still biased if images originate from a small number of patients or a single laboratory. Generalizable evaluation requires diversity in patient demographics, acquisition equipment, clinical sites, and disease presentation. Sampling should occur at the patient level, and the test set should reflect realistic prevalence or be accompanied by prevalence-adjusted predictive values.

F. Implications for Oman

For Oman, a realistic first step is not immediate autonomous deployment but a carefully governed validation program. A national or multi-hospital collaboration could create an anonymized, quality-controlled hematology dataset representing local laboratory workflows. Models could then be externally tested against expert review, with performance reported separately by hospital, equipment type, and clinically relevant subgroup. This approach would generate evidence that is more useful for local adoption than importing an accuracy number from an unrelated benchmark.

VI. PROPOSED CLINICAL VALIDATION FRAMEWORK

A. Dataset Curation and Splitting

Future model-development work should define inclusion criteria, diagnostic reference standards, and image-quality requirements before training begins. Patient-level identifiers should be used solely to enforce train/validation/test separation and then protected or removed according to governance requirements. Data augmentation may increase visual diversity, but synthetic variation must not be treated as a substitute for independent clinical data.

B. Model Development and Baselines

A strong study should compare advanced deep networks with transparent baselines. Classical ML on engineered morphology or laboratory features, a standard transfer-learning CNN, and a more complex ensemble can be evaluated under the same split. Reporting only the best model creates selection bias; all prespecified baselines and tuning procedures should be documented. Hyperparameter optimization must be confined to training/validation data to preserve the integrity of the final test set.

C. Performance and Calibration

The minimum reporting set should include sensitivity, specificity, precision, negative predictive value, F1-score, AUROC, confusion matrices, and confidence intervals. When probabilistic outputs are used, calibration curves and a metric such as Brier score should be included. Results should be presented at the patient level whenever clinical decisions are patient-based. If multiple images are obtained from one patient, image-level accuracy can otherwise give an inflated impression of independence.

D. External and Prospective Validation

After internal testing, the model should be evaluated on a fully independent hospital or time period. Prospective silent deployment is a useful intermediate stage: the system generates predictions without influencing care, allowing researchers to compare outputs with routine diagnosis and identify workflow or distribution problems. Only after adequate prospective evidence should an interventional study evaluate whether the tool changes diagnostic time, error rates, workload, or patient management.

E. Human Factors and Governance

Clinical validation should include healthcare professionals because technical performance alone does not determine adoption. Usability, alarm fatigue, explanation quality, confidence calibration, workflow integration, and responsibility for errors should be tested. WHO guidance

provides an appropriate governance foundation emphasizing safety, transparency, accountability, inclusiveness, and protection of human autonomy [4].

F. Reference Standard and Label Quality

A medical AI model can only be as reliable as its reference labels. For leukemia research, labels may be derived from expert morphology, immunophenotyping, bone-marrow findings, molecular testing, or a combination of evidence. Image labels created solely from one reader's visual judgment can contain uncertainty, especially in borderline cases. Future datasets should document how diagnoses were established, whether multiple experts reviewed difficult cases, and how disagreements were resolved. When label uncertainty is clinically meaningful, forcing every case into a single hard class may hide important ambiguity.

The reference standard should also match the intended task. A system designed to flag abnormal cells for review is different from a system claiming to diagnose a leukemia subtype. The former may use cell-level annotation and prioritize high sensitivity, whereas the latter requires patient-level diagnostic evidence and a much more demanding validation pathway. Precise definition of intended use prevents performance claims from exceeding what the data can support.

G. Domain Shift and Laboratory Variation

Blood-smear images can vary because of staining protocols, illumination, microscope optics, camera sensors, image compression, slide preparation, and technician practice. A network may inadvertently learn site-specific visual characteristics rather than general disease morphology. This phenomenon, often described as domain shift, is one reason that random image-level train/test splits can overestimate performance if images from the same patient or laboratory appear in both sets.

Robust evaluation should therefore include site-held-out or time-held-out testing. If multiple hospitals participate, one hospital can be excluded from training and used as an external test site. Performance drops should be reported rather than hidden through additional tuning on the test data. Domain-adaptation methods can later be investigated, but they should be evaluated against a clearly defined external baseline.

H. Class Imbalance and Clinically Relevant Prevalence

Many research datasets intentionally balance normal and abnormal images to simplify model development. Balanced datasets are useful for comparing algorithms, but they do not necessarily reflect clinical prevalence. Predictive values depend on prevalence, so a model that performs impressively on a balanced benchmark may generate a different proportion of false alerts in routine screening. Future studies should therefore report both balanced benchmark metrics and performance under a prevalence distribution that resembles the intended use environment.

Where rare subtypes are included, macro-averaged metrics can prevent common classes from dominating the result. Confusion matrices should be presented at both cell and patient levels where applicable. Rare but clinically important errors deserve qualitative review even if they have little effect on aggregate accuracy.

I. Explainability as a Clinical Evaluation Question

Explainability should be evaluated with clinicians rather than treated as a decorative visualization. A heatmap that highlights the correct cell region may increase confidence, but it does not necessarily explain which morphological features drove the classification. Conversely, a textual explanation generated by a language model may sound plausible without being faithful to the underlying classifier. Future work should test whether explanations help professionals detect model errors, understand uncertainty, or make better decisions compared with predictions alone.

Useful explanation formats may differ by role. Laboratory specialists may prefer cell-level morphology cues and segmentation overlays, whereas physicians may need patient-level summaries that integrate laboratory findings with uncertainty. The survey sample includes doctors, nurses, and laboratory technicians; future questionnaires could therefore examine role-specific explanation needs rather than asking about general trust in AI.

J. Post-Deployment Monitoring

Clinical AI validation does not end at deployment. Changes in laboratory equipment, staining procedures, patient populations, or clinical workflows can alter the data distribution over time. A deployed system should therefore be monitored for changes in sensitivity, specificity, calibration, and usage patterns. Performance thresholds and escalation procedures should be agreed before clinical use so that the system can be paused or reviewed if drift is detected.

Audit logs should capture model version, input provenance, output, confidence, and clinician action without unnecessarily exposing patient information. Monitoring should also identify whether clinicians consistently override the model in particular scenarios. Repeated disagreement may signal a model limitation, a workflow problem, or a training need and should trigger structured review.

K. Reproducibility and Reporting Standards

Future technical studies should provide enough information for independent replication: dataset source and version, number of patients and images, inclusion/exclusion criteria, split method, preprocessing, augmentation, architecture, initialization, optimizer, learning-rate schedule, stopping rule, hyperparameter selection, and software environment. The source report currently aggregates figures from several studies; reproducible local research will require a single clearly documented pipeline.

Confidence intervals should accompany performance metrics. If models are compared, statistical comparisons should respect paired predictions on the same test cases. Repeated cross-validation can be useful during development, but a final untouched external test set remains essential. Reporting should also state whether model selection was based on accuracy, sensitivity, AUROC, or another prespecified criterion to reduce selective reporting.

L. Proposed Oman Pilot Study

A feasible Oman pilot could begin with retrospective blood-smear images from one institution and an external validation set from a second institution, subject to ethics and data-sharing approvals. Expert hematology or pathology review would define the reference standard. The first model could focus on a narrow triage task—such as distinguishing clearly normal from suspicious smears—rather than attempting autonomous

leukemia diagnosis. Narrow intended use makes error analysis and safety evaluation more tractable.

After retrospective validation, a silent prospective phase could process incoming images without displaying predictions to clinicians. Researchers could compare the model output with routine diagnosis, measure processing latency, and identify cases that fall outside the training distribution. If performance remains acceptable, a later decision-support study could show predictions to clinicians and measure whether the tool changes review time, sensitivity, workload, or disagreement rates. This staged approach produces stronger clinical evidence than moving directly from public benchmark accuracy to deployment.

M. Health-Professional Training and Adoption

The professional survey suggests that familiarity with AI is associated with more favorable perceptions. Training may therefore influence adoption, but education should include limitations as well as capabilities. Clinicians need to understand that a model can be highly accurate overall yet fail systematically on an underrepresented subgroup or unfamiliar acquisition condition. Training should cover confidence interpretation, appropriate override behavior, reporting of suspected errors, and the distinction between decision support and final clinical responsibility.

Trust can be strengthened through transparency about validation and monitoring rather than through promotional claims. Providing clinicians with local validation results, examples of known failure modes, and clear escalation pathways may produce more appropriately calibrated trust than presenting only headline accuracy.

N. Proposed Experimental Reporting Template

A future Oman-based technical paper should report its dataset in a way that separates patients, slides, and image patches. The number of images alone is insufficient because hundreds of patches can originate from a small number of patients. A dataset table should therefore state the number of patients in each class, number of slides, number of extracted cells or patches, acquisition site, staining procedure, imaging device, and reference-standard procedure. Train, validation, and test partitions should be defined at patient level and frozen before final evaluation.

For each model, the paper should report architecture, parameter initialization, input resolution, augmentation, optimizer, batch size, learning rate, number of epochs, early-stopping criteria, and the rule used to select the final checkpoint. If transfer learning is used, the pretrained source and which layers were fine-tuned should be stated. These details are necessary because apparently small implementation choices can produce large differences in medical-image performance and are essential for reproducibility.

O. Patient-Level Versus Cell-Level Decisions

Many leukemia image studies classify individual cells, while clinical decisions are made for patients. A patient may contribute many cell images, and these images are statistically dependent. Future work should define how cell-level predictions are aggregated into a patient-level recommendation. Possible strategies include majority voting, proportion of suspicious cells, attention-based pooling, or rules that incorporate laboratory values. The aggregation method must be evaluated separately because high cell-level accuracy does not automatically translate into reliable patient-level triage.

Patient-level evaluation also changes the interpretation of errors. A single incorrectly classified cell may be clinically unimportant if the overall smear contains many correctly identified abnormal cells, while missing all abnormal cells in one patient is a serious failure. Reporting should therefore include patient-level sensitivity and specificity in addition to image-level metrics.

P. Multi-Modal Opportunities

Blood cancer diagnosis rarely depends on one image source alone. A future system could combine blood-smear morphology with complete blood count variables, patient age, symptoms, or other laboratory measurements when ethically and clinically appropriate. Multi-modal models may improve discrimination when morphology is ambiguous, but they also introduce missing-data and interoperability challenges. A simple, well-validated image model can be preferable to a complex multi-modal model if the additional inputs are inconsistently available.

The design should therefore start from the clinical question rather than the availability of algorithms. If the intended use is smear triage, image data may be sufficient. If the intended use is subtype classification or risk stratification, additional clinical and molecular data may be required. Each added modality should demonstrate incremental value over a simpler baseline through prespecified analysis.

Q. Uncertainty and Abstention

A clinically useful AI system should be allowed to abstain when it encounters an uncertain or unfamiliar case. Conventional classifiers always select a class, even when the input falls outside the training distribution. Confidence thresholds, out-of-distribution detection, or uncertainty-estimation methods can instead route low-confidence cases directly to expert review. This is especially appropriate in hematology, where rare morphologies and artifacts can differ substantially from curated training data.

Abstention creates an important evaluation trade-off between coverage and reliability. Researchers should report the proportion of cases for which the model provides a prediction and the performance achieved at different confidence thresholds. A system that accurately assists on 80% of routine cases and safely defers the remaining 20% may be more clinically useful than a model that attempts to classify every case with poorly calibrated confidence.

R. Clinical Workflow Scenario

One realistic workflow is AI-assisted pre-screening. After a digital blood smear is acquired, the system identifies candidate abnormal cells and presents them in a ranked review queue. The laboratory professional examines the highlighted regions, confirms or rejects the suggestions, and records a decision. The AI output does not create the diagnosis; it prioritizes visual review and may reduce time spent searching large fields. Cases with high uncertainty or discordant findings proceed through normal expert review and confirmatory testing.

This workflow is compatible with the professional perceptions observed in the survey, particularly favorable views of diagnostic speed, monitoring, and decision support. It also

limits the risk of automation bias because the human reviewer remains responsible for interpretation. Future clinical research can compare review time and error patterns with and without AI assistance while keeping the diagnostic reference process unchanged.

S. Economic and Operational Evaluation

Clinical adoption also depends on operational feasibility. Deep-learning systems require hardware, software maintenance, model monitoring, cybersecurity controls, and staff training. A future Oman study should estimate the cost of image digitization, inference infrastructure, validation, and ongoing governance rather than considering algorithm accuracy in isolation. Benefits should likewise be measured in operational terms such as time saved per smear, reduction in repeat review, or ability to prioritize urgent cases.

Economic analysis should not assume that faster classification automatically lowers cost. If an AI system generates many false alerts, requires extensive manual correction, or depends on expensive imaging infrastructure, total workload may increase. A prospective pilot should therefore collect workflow time, number of manual interactions, system downtime, and maintenance burden alongside diagnostic metrics.

VII. LIMITATIONS

The primary survey is small (N=32) and measures perceptions rather than clinical outcomes. The professional distribution is useful but does not substitute for a representative national sample. The study is cross-sectional, so familiarity and positive attitudes may influence each other in either direction. Some technical performance values in the source report originate from heterogeneous published studies and public datasets rather than a single reproducible local experiment, making direct model comparisons inappropriate unless datasets and protocols are harmonized. Finally, no prospective Oman-based clinical validation is reported.

VIII. CONCLUSION AND FUTURE WORK

AI has substantial potential to support blood cancer detection, particularly through automated analysis of blood-smear images and other hematology data. The surveyed healthcare professionals were generally receptive to diagnostic-speed, monitoring, and decision-support applications, and prior AI experience was associated with more favorable perceptions. These findings support further investigation but should not be interpreted as proof that an AI system has already improved patient diagnosis in Oman.

The next stage should establish a reproducible local validation pipeline: curate representative patient-level data, benchmark transparent and deep-learning models under the same protocol, report clinically meaningful metrics and calibration, perform external validation, and prospectively evaluate workflow integration. AI should remain a decision-support technology under professional oversight. A publication-quality contribution in this domain is therefore not the highest isolated accuracy figure, but a transparent chain of evidence showing that a model is accurate, robust, fair, understandable, and safe in the setting where it will actually be used.

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The Impact of Digital Integration on Consumer Confidence and Purchase Intent in Sustainable Home Farming in Oman

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Abstract

This study aims to understand how digitization influences consumer trust and purchase intention toward sustainable home farming in Oman. Achieved through IoT solutions bridging the gap known as the "Biological Black Box." The objective of this study was to identify barriers that prevent aquaponics from proliferating throughout Oman among young professionals. Urban topics including but not limited to water chemistry frustrations and the stress of things going offline. Data was collected using quantitative methods through a 30 respondent online survey. From our results we found that although there is great interest in sustainable farming. Its application could be limited by what we have identified as the "Confidence Gap" and high maintenance of manual operations. Another interesting finding was what we have identified as the "Digital Lift." Once real-time health score dashboards and cell notifications were introduced. The odds of purchasing shifted from unlikely to very likely by almost a 50% increase. From this we can conclude that implementing technologies that focus on consumers will help localize food security in Oman Vision 20.40.

Keywords - Internet of Things, aquaponics, sustainable agriculture, consumer confidence, purchase intent, smart farming

I. INTRODUCTION

Food self-sufficiency rate: Oman's national ability to grow/produce what it needs to eat within its borders. Oman Vision 20 forty hinges upon food self sufficiency. The country desires to sustainably grow enough food to support itself and limit imports in times of worldwide crisis etc. Oman had an average FSMR of 65.8% in the year 20 twenty-four however ...Oman has an arid climate with temperatures regularly reaching 45°c... Fresh water is extremely limited in Oman". A small-scale closed system home farming method known as aquaponics offers urban residents of Oman a chance to help their country limit water use by up to 90% while growing their own food at home. Despite many knowing about aquaponics systems and seeing the financial savings and planet positive impact of this technology many consumers are lost in the mind shift of taking aquaponics systems from a hobby they know nothing about to a mainstream consumer товар. Omani's see aquaponics systems as a "black box". They cannot see the chemistry happening inside (nitrogen cycle, bm/pH swing etc.) With no visible signs that something may go wrong consumers see huge risk in investing in these systems. If they cant "see" what is happening in the ecosystem, they take care of it when things go wrong. Fish died? Add water. Plants wilted? Add nutrients. This, combined with the high perceived demand for manual technical skills is the problem killing conversion (purchasing desire). This study solves these problems through digital integration. We will connect the aquaponics system to a centralized IoT (Internet of Things) type application. Turning this kitchen install into more of a smart appliance. By introducing data into the once "black box", we are expecting to see at least a 60% decrease in manual maintenance and a 100% increase to your windows of stability by proactively alerting users to imbalances before they become fatal. This study hopes to quantify the consumer behavioral shift when approached with a DIGAssisted system versus a traditional manual system and PROVE that technology is the driving factor for consumer purchase. In the Sultanate of Oman, the intersection of food security and technological innovation has become a national priority under Oman Vision 2040. With over 60% of Oman's food currently imported, the government has pivoted toward "Smart Agriculture" to build a resilient, self-sufficient food system. Aquaponics a soil-less farming method that uses 90% less water than traditional agriculture is uniquely suited to Oman's arid climate and limited freshwater resources. As of 2026, the Omani aquaculture market is valued at approximately USD 672 million, reflecting a growing national commitment to sustainable protein and vegetable production.

While this national scale progress has been happening, there's a large deficit within the home-urban farming industry. As more and more youth across Oman venture into home farming in Muscat, Suhar, and Al Rustaq cities rooftops and backyards, they're met with harsh environmental conditions. Highs of over 45° daily in the summer months for those living in interior cities and high humidity along the coastal cities. These extreme changes in temperature leave both your fish and plants susceptible to damage. One power outage or accidental spike in water pH can crash your system. When you factor in that The Smart Home market in GCC will reach $438.6 Million By 2034 Growing at a CAGR of 10.8% through the forecast period., it shows that consumers in Oman are primed for holistic digital integration. What's missing is localized research that demonstrates how an IoT connected mobile application can act as a solution to these living systems. Enabling notifications that alert the user in real-time and cut hours of manual labor by 60% could shift the whole concept of aquaponics from gimmicky Raspberry Pi experiment to a dependable "smart appliance" that successfully closes the gap between OMAN's food security initiatives and the individual consumers capacity to farm at home. This study aims to provide the quantitative data on how much of an impact this type of technology has

A. Problem Statement

One of the key issues that have caused low technology adoption of the technology in Oman has been described as the "Technical Confidence Gap." For most families living in Oman, the technology still feels like a biological "black box" that takes chemistry and biology skills to operate. Because traditional monitoring methods require manual reading and adjustments, at-home aquaponics cannot be sustained in Oman due to the busy schedules of the nations professionals. Without a way to remotely monitor the systems status, failure rates will likely feel high and Purchase Intent will remain low. Aquaponics has been described by many as a potential solution to urban food security and environmental waste through sustainable home farming. But until the "Biological Black Box" issue is addressed, market adoption will continue to be dismal. When using traditional methods to manage the system, you cannot see the chemical reactions happening that transform ammonia into nitrates with your eyes. Manual management means lots of time understanding technical requirements, frequent chemical testing, and spending many hours babysitting your system. This instills the fear of the unknown into the average consumer. If I mess up the pH or temperature it will cause everything to die they think. Due to a lack of "Real-Time Visibility" and "Self-Efficacy" consumers feel, their "Purchase Intent" is low. They believe that aquaponics is a high-risk, difficult task rather than comparing it to buying another household appliance. Unless the information gap and maintenance burden is replaced by some type of automatic digital controller, home aquaponics will never reach mainstream consumer status.

B. Research Aim & Objectives

The hypothesis tested in this study was that supplementing a home aquaponics system with an IoT-based monitoring + automation app

will enhance customer trust and purchase decisions by turning the complex biological stewardship of aquaponics into an open, accessible digital experience. The following objectives will help answer this research question:

Objective 1: Explore "Trust": Explore what exact elements of the biosystem's biological and technological fail points (fish death, water chemistry failure, etc.) are currently causing hesitation in potential customers from purchasing traditional aquaponics units.

Objective 2: Design & Simplify Digital Window: Design a digital window into aquaponics that converts sensor readings into easy to read "Health Scores" in order to increase user self-efficacy.

Objective 3: Track Time Saved: Demonstrate that automating routine tasks (lighting, feeding, logging) can decrease time spent on maintenance by 60%. Then, evaluate how much of an impact this converted "free time" has on a consumers willingness to adopt the technology.

Objective 4: Test “Failure Rate”: Demonstrate that app-mediated predictive alerts can increase the length of the ecosystem's "Stability Window" by 100%. Increasing the customers perceived reliability of the product and long term value.

II. RELATED WORK

Healthy food production encouragement tendency all over the world drew much attention in the Sultanate of Oman. As Oman is one of the driest countries in the world with a lack of freshwater resources, food security, dependency, and sustainable agricultural self-sufficiency initiatives became Sultanate's Oman Vision 2040 focus. Large farms cannot meet all needs; therefore, sustainable home farms became another effective way to grow your food securely and sustainably while having less impact on the environment. However, there is one major issue that is restricting sustainable home farms developing process, and that is consumers' trust and confidence lack. Some customers are afraid of failing their crops due to weather conditions and the lack of skills. Fortunately, there is a new developing method that can eliminate the issue mentioned above. IoT technology can help Omani citizens grow their productive gardens by using real-time sensors and automation. So, consumers would grow their plants based on knowledge instead of guessing by managing their gardens manually. Hence, the purpose of this research is to analyze how the mentioned digitalization can affect consumers' trust and their intentions to start home farming.

As IoT devices become more commonplace, there have been opportunities to leverage this technology for advanced agricultural monitoring, automation, and resource management. Previous literature has found that sensor-based monitoring can acquire environmental data and relay that information to users on a continuous basis [2]. Researchers from a 20 last year study featured in Sensors used IoT technology to monitor smart agriculture devices by using environmental sensors and analyzed data using cloud-computing [1]. The environmental parameters that were tracked included temperature, humidity, and water quality. The sensor framework allowed users to have current information about their growing environment. Results from this study concluded that IoT-based monitoring can increase efficiency, limit manual monitoring, and allow users to make better decisions by limiting unknowns about changing environments.

While clearly beneficial, research presented in [1] judges performance of the system from a technical perspective. Far less consideration is given to how users without technical backgrounds interact with such technologies or if they would be comfortable relying on automation's suggestions. This gap becomes all the more relevant when IoT technologies make the jump from commercial agriculture settings to those which can be implemented at home. Users may not fully adopt a home aquaponics system if it has a high technical degree of reliability but they do not understand what information it provides them or trust that its recommendations/actions are accurate. User trust, perceived usefulness, and ease of use are important variables that are understudied in technically focused smart-agriculture research.

Automation has also been explored as a method for decreasing human effort required for agricultural operations. Research published in Procedia Engineering [2] implemented an automated smart-farming solution that combined IoT sensors, actuators, and irrigation/environmental controls. Experimental results from their prototype proved that automation was able to increase precision of agricultural operations while decreasing human labor. Additionally, automated irrigation allowed for decreased water consumption as resources were allocated based on monitored conditions rather than a set schedule or manual control.

While the results presented in [2] show practical promise for agricultural automation, the system they describe was designed principally with conventional or comparatively large-scale agricultural settings in mind; portability and suitability for small household systems was not the main focus of their research. In addition, there is relatively little discussion of automated agriculture from the viewpoint of non-technical end-users. This represents an important gap for systems used in home-occupations like aquaponics, where end-users may have limited prior exposure to water chemistry, fish medicine, plant nutrition, IoT systems etc. Automation of these activities can ease the burden of labour, but a system which operates automatically without clearly explaining its behavior can be equally cause stress or uncertainty. For this reason it may be necessary to pair automation with user-centered interfaces that help non-expert users understand system behavior.

In addition to technological advances supporting smart agriculture techniques, aquaponics has been identified as an area of interest. The authors in [3] conducted a review on aquaponics systems environmental sustainability, finding several benefits from combining aquaculture with hydroponic growing techniques. When operated in conjunction, the waste-heavy water produced by fish can be employed to grow plants, and in turn, these plants can filter and recycle water for the fish. Benefits from this symbiotic relationship can lead to reduced water usage and nutrient recycling when compared to traditional growing operations. This has allowed aquaponics to gain interest in countries where freshwater resources and sustainable food production are of concern.

However, existing literature cited in [3] also points to numerous usability challenges impeding aquaponics adoption. Achieving the symbiotic balance between fish, plants, microbes, water parameters, and nutrient cycles may be challenging for novice operators. Tuning the system to run effectively may involve constant monitoring and awareness of numerous biology- and environment-related variables. To the residential user, many of these working processes occur within a larger biological black box: they can see that the system is running, but may not have enough information to understand why conditions are changing as they are, or what steps to take when something goes wrong. Although research has verified the environmental benefits of aquaponics systems, much less has been explored in terms of making these biological processes more manageable for the average user. This points to an opportunity for technology to increase accessibility by bridging the gap between raw sensor readings and digestible information, suggestions, and notifications.

This constraint can also be seen in previous IoT implementations of agricultural monitoring systems. The authors in [4] explored an IoT monitoring framework that enabled sensing of temperature, humidity and moisture. This framework proposed utilizing a CC3200 microcontroller with environmental sensors and an online portal to monitor farms remotely. The prototype showed that real-time monitoring allowed for smarter irrigation scheduling as well as enabling pumps to turn on automatically after reaching threshold environmental conditions. This lessens the need for manual monitoring while demonstrating use cases of integrating sensing technologies with farm controls.

Still, contributions from [4] continue to be restricted to sensing and automation at the hardware level. The solution reacts primarily to live measurements and predetermined thresholds, rather than useful information based on historical patterns or predictions about the future. Additionally, not much emphasis is placed on relaying sensor measurements in a manner that users can understand. While

simply displaying raw measurements may work for farmers with technical backgrounds, it can be challenging for household users to make sense of moisture measurements, temperature deltas, pH, or WQI readings. As such, an effective residential agriculture platform should do more than just tell the user what its sensors are reading. The raw data should be contextualized into useful messages that describe what is happening with the system and prescribe an appropriate course of action (if any).

Technologies for sustainable agricultural automation have also been studied in self-watering systems that utilize renewable energy sources to operate. Presented at an IEEE conference, the study published in [5] presented a self-watering agricultural automation system. The intent was to cut down the need for both hand-watering crops and using traditional energy by coupling an automated watering system with solar power. This could allow for agriculture to take place in areas that have water restrictions or lack access to stable electricity.

A similar idea was proposed in [5]. This innovation was applicable to resource- efficient agriculture since it involved optimization of both water and energy use. However, self-watering addresses only one aspect of the larger management issue. With aquaponics there are many variables which need constant monitoring and cross-dependency between water level, water temperature, water quality, fish health and welfare, and plant needs. True domestic aquaponics solution must include more than just automated watering schedules. We need a fully integrated digital ecosystem that can measure different parameters, recognize when something is off and convey that information to the end user in an actionable manner.

Taken together, references [1]–[5] suggest IoT sensing, automation, cloud connectivity and renewable- energy technologies can increase efficiency and sustainability of modern agriculture practices. Many of the technical hurdles have been met head on in past research focusing on real-time environment monitoring, automated irrigation, resource conservation, and decrease on manual labor requirements. Past aquaponics research has also proven promising as a method to conserve water and recycle nutrients.

Nonetheless, an issue present throughout the literature is their heavy focus on technical operation and capabilities over user experience. Current systems often fail to account for the need to explain sensor measurements, biological statuses, or automated operations to end-users. This is especially true of household aquaponics since end-users may not be familiar with agriculture/aquaculture/IoT technology/water-quality management concepts.

A second critical research gap deals with consolidation of these technologies into one consumer-focused platform. Most literature pertains to monitoring, automation, irrigation, sustainability, or renewables individually. Few researchers have explored how combining these functionalities could tackle both the biological complexities of aquaponics and optimize usability and consumer trust. The task, then, is not just to measure more parameters but to convert that information into data consumers can understand.

The main gap identified above has been explored in this work by delving into IoT technologies with regards to their digital integration in domestic aquaponics systems focusing on real-time monitoring, automation, explainable user-feedback and trust. Instead of assuming users are bystanders that simply observe measurements derived from sensors, we discuss how digitalisation could make aquaponics less overwhelmingly complex to interact with consciously. This research questions build upon past technical understandings by approaching aquaponics through a user-centered lens.

III. RESEARCH METHODOLOGY

Our research framework comprises a mixed-method comparison study aiming to assess if adoption rates and customer confidence towards aquaponics at home can be increased through the application of Internet of Things (IoT) technology. We will conduct this assessment through collected survey statistics, qualitative commentary, as well as a feature-by-feature comparison of a standard aquaponics ecosystem with its IoT-equipped counterpart. We will specifically focus on if real-time monitoring, automated maintenance, simplified data presentation, and mobile updates alleviate the apprehension users face towards the complex biological and environmental nature of an aquaponics system.

A. Research Objectives

Five specific aims have been formulated to guide the study: 1) Determine biological and technical hurdles perceived by consumers that may inhibit adoption of traditional home aquaponics units. Biological and technical challenges included fear of fish death, fluctuation of water chemistry, system crash or failure, time invested in maintenance, and technical expertise necessary to ensure proper living conditions.

Secondarily, research determines whether or not an IoT-based application could adequately convert collected sensor readings of dissolved oxygen, water temperature, and pH readings into basic terms that can be easily read and understood by everyday users. The mobile application interface proposed specifically utilizes a system Health Score to give users a general idea of how healthy their aquaponics system is.

Third, the research is interested in determining if automation of mundane maintenances tasks can alleviate the degree of human work necessary to run a home aquaponics system. More specifically, does the user welcome the idea of a system that largely alleviates day-to-day maintenance tasks.

Fourth, the perceived usefulness of receiving real time notifications if left in the dark about rising temperatures or sudden pH swings. Will users feel more aware of their system's conditions and feel they have enough time to take action before the issue becomes dangerous?

Lastly, the study seeks to contrast consumer purchase intention toward traditional aquaponics systems and consumer purchase intention toward IoT-enabled systems. Will the integration of digital technology allow the idea of home aquaponics to feel like something of added value thus helping it to be accepted in the market?

Those goals are applicable to Oman given its efforts towards sustainable water use and food security at the national level. While home aquaponics could provide Omani consumers a resource-efficient method to grow food, a major barrier is its potential users' lack of confidence in their ability to manage aquaponic systems. Their difficulty in understanding or believing what happens within the aquaponic system is what this study terms the biological black box of fish, plants, microbes, and water chemistry.

B. Research Design

A quasi experimental mixed-method approach is used to study the influence of digitalization on consumer perception of home aquaponics systems. Two system set-ups are conceptually compared: a baseline aquaponics system which would typically demand more frequent manual monitoring and an Internet of Things (IoT) enhanced aquaponics system equipped with various sensors, automatic monitoring, alerts, and streamlined digital output.

In studies where participants interact with the systems themselves, they are introduced to both system set-ups in similar circumstances so that variances in perception can more confidently be linked to the presence of digital features. This comparison allows for an analysis of if and how transparency and lower maintenance effort impact trust and intention to buy.

Mixed methods are used to further analyze how consumer attitude, perceived effort, trust, technology readiness, and intention to buy are affected. While quantitative data allows for this analysis, qualitative answers can help illustrate concerns, expectations, and desired features among consumers.

C. Theoretical Framework

The research questions that follow draw from the Technology Acceptance Model (TAM), as outlined by Davis [6]. The TAM states that perceptions of usefulness and ease of use are the biggest

predictors of technology acceptance. This theory applies well to home aquaponics, as people may be dissuaded by maintaining a biological system, instead of noticing energy and water efficiencies of the technology itself.

For purposes of this study, digital integration will be treated as the independent variable. Digital integration includes: IoT sensors and real time environmental monitoring, push notifications to mobile devices, automated maintenance features, and simplified user-facing information.

Consumer confidence and purchase intention are the dependent variables. Consumer confidence is self-reported trust that a user can understand, view, and control their aquaponics system. Purchase intention is self-reported interest in buying and using an aquaponics system.

The hypothesis provided conceptually relates these variables by suggesting that digital integration allows for visibility into what would otherwise be a black box of biological processes. This visibility, as well as automated features, can lead to users feeling more comfortable with their ability to understand and maintain the system. Greater confidence in aquaponic systems can lead to higher intentions to purchase them.

Therefore, the conceptual relationship is as follows:

Digital Integration → Noticeability of Complexity → Consumer Confidence → Purchase Intention.

D. Research Questions and Hypotheses

To measure research goals and objectives, this study is structured around the following research questions:

RQ1: What biological and technical barriers deter consumers from adopting conventional home aquaponics systems in Oman?

RQ2: Can IoT-based remote monitoring and simplified system visualization increase users' confidence in operating aquaponics systems?

RQ3: How does perceived reduction in maintenance effort impact consumer willingness to adopt an IoT-enabled aquaponics system?

RQ4: Can real time-notifications and digital grower instructions lower perceived anxiety about system failure?

RQ5: Are IoT-enabled aquaponics systems likely to garner greater consumer purchase intention than conventional aquaponics systems?

Using these research questions as a foundation, this study aims to statistically evaluate the following hypotheses:

H1: IoT-based digital enablement is positively correlated with consumer purchase intention toward home aquaponics systems.

H2: Perceived reduction in maintenance effort is positively related to willingness to own an IoT-based aquaponics system.

H3: Remote monitoring, simplified visualization of system data and receiving system notifications are positively related to confidence in operating a home aquaponics system.

Each hypothesis will be tested based on collected survey data and system comparison data. Hypotheses are not presupposed to be accepted for the purposes of this study.

E. Participants and Sampling Strategy

The population includes potential consumers living in Oman who may have an interest in sustainable living solutions, smart home technologies, or home-grown food production. The research especially targets younger consumers who live in urban areas or developing cities and are familiar with new technologies. These cities include Muscat, Suhar, and Al Rustaq.

A convenience sample will be used for this study. As this study is exploratory in nature and it is relatively easy to access participants who fit within the target demographic, a convenience sample will be used. The sample size is 30 respondents. This sample size is adequate for this initial study to gauge consumers' perceptions. However, because this is a small sample and it is not a probability sample, the results cannot be generalized to all Omanis.

Participants from various backgrounds will be asked to participate in the study when allowed to increase variation in responses. Ages and areas of residence will be recorded to allow for demographic comparisons.

F. Data Collection Methods

A triangulation strategy is adopted by combining quantitative, qualitative, and system-oriented data. The use of multiple data sources enables research problems to be examined from both technological and consumer perspectives.

1)Questionnaire Survey

A structured questionnaire serves as the primary quantitative data collection tool. Survey questions assess respondents' familiarity with smart technologies, perceptions of conventional aquaponics, concern over biological and technical complexity, attitudes towards IoT-enabled functionalities, and purchase intention.

Participants' responses to most perceptual questions are captured using a five-point Likert scale so they can be translated into numbers for further statistical analysis. Comparison questions between conventional and IoT-enabled systems gauge differences in reported purchase intention and perceived confidence.

2) Qualitative Feedback

Open-ended questions (and when necessary semi-structured interviews) are administered to collect additional data on study participant worries and desires. Some worries and desires we specifically probe include concerns or questions not easily asked with fixed-response questionnaire items (i.e., fear of killing fish, water chemistry being too complicated to understand, maintenance anxieties, and desired smart-functions). We also ask open ended questions to let respondents provide feedback on features they find desirable such as automated cleaning, smart notifications, easy to follow directions, as well as any other functions they think could make home aquaponics more usable.

3) IoT Monitoring Components

This envisioned IoT-based aquaponics setup consists of sensors which would measure dissolved oxygen content, water temperature, and pH. The technical details of measuring these variables enable the real-time monitoring functionality as well as Health Score interface described above.

Rather than expecting users to analyze each of these values on their own, the digital readout could display information about the state of the system in an abstracted way. Additionally, the mobile device could send push notifications if any of the watched variables fall outside of a healthy range so users can address undesirable conditions more rapidly.

G. Instrument Validity and Reliability

There are some measures that can be employed in order to help ensure a high quality of data-collection instrumentation. Content validity can be ensured by basing questionnaire items on the study objectives and constructs to be measured; in this study these are drawn from TAM and include perceived ease of use, usefulness, confidence and behavioral intention.

Additionally, the questionnaire could be piloted to a small number of respondents prior to wider administration in order to identify any questions which may be ambiguously-worded, duplicated or difficult to interpret. Responses from such a pilot could then be used to improve the consistency and readability of the instrument.

Where a construct is measured using multiple items based on Likert-scale questions, internal consistency reliability could be measured using an appropriate statistic such as Cronbach's alpha, if enough related questions are included in the questionnaire. Likewise, sensor-based measures will allow for more consistent readings than subjective manual observations of environmental variables such as temperature and pH.

H. Data Collection Procedure

The survey is sent electronically to users in Oman. Respondents are given adequate information to understand the difference between the traditional setup and the IoT enabled aquaponics system we are proposing before they answer the comparison questions.

Respondents then rate concerns with traditional aquaponics and express their opinions on proposed digital features like remote monitoring, push notifications, Health Score display, and low maintenance needs.

Answers are anonymized where possible and compiled for statistical and thematic analysis. Blank, repeat, and obviously spam responses are discarded from the analysis they do not contribute to.

I. Data Analysis

The data analysis process consists of several stages, including data preparation, descriptive analysis, comparative analysis, association testing, and qualitative thematic analysis.

1) Data Preparation

Data from questionnaires were first screened for completeness, internal consistency and fitness for analysis. Responses to Likert-type questions were coded on a five-point scale from 1 to 5 with higher scores indicating more agreement or stronger intention to perform the behavior as relevant. Where necessary, categories of demographic variables such as age and location were created to allow for subgroup analyses.

Conceptually related questions within the questionnaire were combined into a single variable if it was theoretically sound and statistically feasible.

2) Descriptive Statistical Analysis

Descriptive statistics were applied to illustrate respondents' demographic characteristics and survey responses. Frequencies, percentages, means, and standard deviations (where appropriate) are reported for levels of technological familiarity, perceived barriers, consumer confidence, and purchase intention. Descriptive analyses will be particularly helpful in determining the most frequently perceived barriers to home aquaponics adoption including maintenance difficulty, inability to recognize system failure, water-quality management, and fear of Oman environmental elements.

3) Comparative Analysis

A comparison is made between participants' purchase intent levels between conventional aquaponics systems and IoT-Enabled aquaponics systems. The difference in consumer reaction pre and post digital features being introduced is termed Digital Lift within this study.

Instead of simply using differences in percentages, a proper paired statistical test can be conducted where respondents rate both options. Either a paired samples t-test or non-parametric equivalent (such as Wilcoxon signed-rank test) can be used depending on distribution and measurement properties.

4) Association Analysis

Relationships among variables such as perceived usefulness of notifications, confidence, perceived complexity, maintenance effort, and purchase intention are examined using appropriate correlation techniques.

Because Likert-scale data are ordinal, Spearman's rank-order correlation may be more appropriate than Pearson correlation when assumptions of interval-level measurement and normality are not satisfied.

The analysis therefore distinguishes between a percentage of respondents agreeing with a statement and a statistically demonstrated correlation between variables. A high percentage of agreement alone is not interpreted as evidence of statistical correlation.

5) Predictive Analysis

Where the available sample size and data quality permit, regression analysis may be explored to investigate whether measures of digital integration, perceived complexity, or consumer confidence predict purchase intention.

However, given the relatively small sample of 30 respondents, regression findings should be interpreted cautiously and regarded as exploratory. The study does not claim causality solely from regression coefficients or survey associations.

6) Qualitative Thematic Analysis

Responses to open-ended questions will be thematically analyzed. Data will be coded based on similar concepts identified in responses, and codes will then be clustered into themes. Possible themes include automation, ease of maintenance, reliability of the system, easier monitoring, real time alerts, and end-user concerns about biological intricacies. Qualitative findings will further support quantitative data by identifying reasons why certain digital aspects could impact end-user perceptions and adoption.

J. Ethical Considerations

All appropriate research ethics guidelines should be maintained throughout the research process. Participation in the research should be voluntary and respondents should be informed of the purpose of the research prior to supplying any data. Information that could reveal the identity of respondents should not be requested unless necessary and information gained from respondents should only be used for the stated academic purposes of this research.

Potential respondents should also be allowed to withdraw from the study at any time without penalty. If required, researchers should obtain institutional ethical approval and ensure that data collection occurs in compliance with their university's research ethics policies.

K. Methodological Limitations

There are several limitations that should be noted. First, our sample size is relatively small (N = 30) and participants are recruited using convenience sampling. As a result, our estimates cannot be generalized to produce inferential statistics about the population of Oman; they merely offer insight into consumers' perceptions. Second, purchase intention was assessed using self-report measures and should not be taken to imply actual purchase behavior.

Third, participants' assessments of the proposed IoT system are based on the hypothetical scenario of using the system as described or demonstrated in this study, not on long-term experience with the system.

Despite these limitations, using a mixed-method approach to compare groups allows us to adequately test whether perceived digital integration, complexity, and consumer confidence affect consumers' willingness to purchase home-based aquaponics technology. Our methods also lay the groundwork for future research by providing preliminary data that can help us design an experimental study with a larger sample.

IV. RESULTS

Results:

The following section displays the results gathered from the 30 responses. Included are participant demographics, knowledge of smart home technologies, perceived difficulties with traditional aquaponics, reaction to proposed IoT-capabilities, and stated purchase intention of both traditional and smart aquaponics systems.

A. Cleaning Data

When ensuring that all responses were completed, Likert-scale questions were assigned values from 1-5 to normalize the responses for analysis. Open-ended responses were also checked to ensure no trivial submissions were submitted for qualitative analysis.

Demographics such as age and the governorate that participants reside in were broken into categorical data. This will allow for group analysis between participants. Next questions regarding perceived complexity, system confidence, and purchase intention were analyzed to determine key drivers of consumer perception of home aquaponics.

B. Participant Characteristics and Technological Readiness

The demographics portion of the questionnaire revealed that the sample contained largely young participants. Just under 73.3% of participants were between the ages of 18 and 24 years old. Given that this generation of Omanis is likely to have the highest degrees of exposure to digital technology, this study was able to effectively

survey the perceptions of the population that would be most likely to use smart greenhouse technology. Country-wise distribution of participants showed that 46.7% were from Muscat and 23.3% were from Al Batinah North Governorate. Participants from other regions made up the remaining percentage of the sample.

The significant concentration of participants from Muscat and other largely urban areas should be noted when considering the results as familiarity with and access to smart technologies can vary from region to region. This study also noted that there was a relatively high base knowledge of smart technologies. Just over three-fourths of participants (76.7%) had previous experience with some form of smart- home technology such as remotely controlled lights, temperature management systems, or automatic monitoring applications.

This suggests that participants were, for the most part, already familiar with the concept of digitally controlling devices within the home. While this base knowledge of smart technology may translate to an appropriate knowledge base for IoT enabled home agriculture, familiarity with smart-home technologies does not mean that participants were familiar with aquaponics or raised awareness of the requirements for raising both fish and plants.

C. Perceived Barriers to Traditional Aquaponics

While study respondents indicated high technological awareness, our findings also identified some user perceptions that could inhibit the operation of traditional home aquaponics systems. One-third of our respondents selected a neutral option when presented with the statement "I would buy a traditional aquaponics system." This does not necessarily indicate that these users would not use aquaponics but could mean they are unsure of what is required to maintain a traditional system. Respondents were most concerned about something going wrong without their knowledge. Just over half of our respondents selected either strongly agree or agree when responding to the statement "I would worry that I would not notice something was wrong with the system soon enough to prevent permanent damage." This finding was somewhat unexpected as one of the appeals of aquaponics is that there is no need to tend to the system constantly because of the nature of balancing living organisms and their environment.

Hands-on management of water quality was another concern for participants. Just over half of our respondents selected either strongly agree or agree with "checking water chemistry seemed like it would be too difficult or time-consuming." For someone who has never kept fish or monitored farm plants, the perceived stipulations of aquaponics, such as checking pH and other water parameters on a frequent basis, could deter them from seeing aquaponics as an option. Environmental factors also proved to be a respondent concern. Forty percent of respondents selected either strongly agree or agree with "I am concerned that high temperatures during Oman summers would affect system performance." This finding leads us to believe that some potential users may believe traditional aquaponics requires active monitoring, especially during extreme temperatures. Together, these findings help to define the existence of what we have coined the biological black box. Users may understand the appeal of aquaponics but may not know how to watch for or know what is happening in the biology of their system.

D. Perceived Value of IoT-Based Monitoring

This preliminary feedback shows that participants reacted positively to some of our recommended features designed to limit uncertainty and increase transparency of the system.

54 out of 95 respondents (56.8%) agreed that receiving instant text message alerts of abnormal water-quality or temperature levels would make them feel less worried about something going wrong in the system. We can interpret this as instant notifications allowing users to feel more in-tune with their system when they are not able to be there physically.

Respondents were also receptive to our proposed Health Score interface. 38 out of 95 respondents (40%) agreed that having a dashboard that calculated and displayed the overall 'health' of their system would make them feel more confident operating their aquaponics system.

This is significant because the Health Score was designed to translate several water-quality parameters into an at-a-glance representation of system status. Instead of expecting non-expert users to understand what individual pH, dissolved-oxygen, and temperature values mean, we can provide an easier way to tell if their system requires attention.

Lastly, 41 out of 95 respondents (43.2%) said they would be more inclined to try home aquaponics farming if there was a mobile app that could give them digital guidance on how to manage their system, including making water adjustments. This further highlights the value of having decipherable recommendations in addition to monitoring.

E. Maintenance Effort and Adoption

Maintenance Effort was another topic that arose as a consideration for participants. Maintenance was raised by roughly 36.7% of respondents as an area where decreased effort would impact their purchase decision. Reducing maintenance effort was specifically associated with keeping daily engagement to about 10 minutes through automated system monitoring and management.

This does not imply that the concept presented has been validated to reduce maintenance time by 60%. It suggests that respondents view decreased effort as a requirement of the consumer. Validation of actual time reduction would come from prototype testing in a controlled environment.

F. Purchase Intention Comparison

Stated purchase intention was compared before and after IoT features were described to provide initial insight into changing attitudes with increased digitalization.

Out of respondents, 13.3% were very likely to buy a conventional aquaponics system. When IoT capabilities were described including monitoring, automation, digital coaching, and notifications, 20.0% of respondents were very likely to buy the system.

That is an increase of 6.7 percentage-points in the bucket representing the highest level of purchase intent. For the purpose of this study, this increase will be referred to as a Digital Lift. It is the lift in stated purchase intent that was observed after introducing digital capabilities. However, this was ANOVA without a subsequent inferential test, so the Digital Lift should be considered descriptive data, not proof of a significant effect.

Digital features appear to have the largest impact on respondents that stated no intention of buying a conventional system. This implies that digital features can address barriers that prevent customers from buying at all. Additional insight was provided by open-ended questions, detailed below.

G. Qualitative Data

Popular Answers. The free-response section allowed participants to describe the features they would find attractive in a smart aquaponics system. The most popular concepts included automated cleaning, easy maintenance, smart monitoring, real-time notification, and fully autonomous systems.

Themes. The free-response answers were separated into categories based on common themes. The themes included automation, easy maintenance, reliability, simplified data/information, and monitoring.

The qualitative data supports the percentages seen in the survey. Participants were looking for ways that technology could make the system easier to use, not simply technology for the sake of technology. Consistent with this, the overall sentiment of open-ended responses indicates that complexities around maintenance, reliability, and required attention detract from purchasing an aquaponics system. IoT capabilities that could address these concerns were viewed as substantial value-adds.

V. DISCUSSION

These results represent an initial investigation into potential drivers of domestic consumer adoption of IoT-enabled home aquaponics in Oman. Broadly speaking, these results indicate that consumer reluctance to adopt home aquaponics technology is less a function of disinterest in sustainable food-production technology and more a question of confidence in operating and maintaining a biologically complex system. The co-development of monitoring + automation capabilities, simplified visualization, and IoT-mediated guidance addresses multiple concerns.

A. Evidence for Biological Complexity as an Adoption Barrier

Perhaps the most significant result of this survey is the uncertainty participants displayed towards monitoring the biology of an aquaponics system. Both the 60% of participants who expressed concern about unknowingly experiencing a system malfunction and the 53.3% who found manual water-chemistry testing difficult/time-consuming support operational complexity as a valid barrier to adoption.

This sentiment validates the theory behind this study's concept of a biological black box. While most smart-home appliances are limited to machine-on-machine interactions, aquaponics technology requires the owner to be aware of living processes that can vary on minute-to-minute basis. Parameters like water chemistry, fish and plant health, temperature, oxygenation, and others all influence one another.

While seasoned aquaponics growers may find intuitive insight in individual measurements, those measurements may overwhelm novice indoor growers if they lack obvious interpretation. This concept validates the smart-agriculture research gap identified in the literature review. While past studies have demonstrated the technical utility of smart farming sensors/automation, relatively little research has focused on converting raw data into household-friendly information.

B. Digital Transparency and Consumer Confidence

Results from user reactions to mobile notifications and the Health Score concept align with the need for system transparency through visible behavior.

57% of participants stated they would be less worried about system failure if mobile notifications were available. This implies that continuous digital surveillance can act as both a technical form of alert for when things behave unexpectedly, and a method of reassuring users and reducing uncertainty.

40% of participants were receptive to the Health Score dashboard concept as well. This insight can translate into design considerations. A successful home aquaponics system should not demand users to manually interpret various disparate sensor readings. Raw environmental data can be distilled into easy-to-understand indicators with supporting context and suggestions for action.

These results can also be loosely associated with constructs in the Technology Acceptance Model. Reduced cognitive load and effort through simplified information and automation could lead to higher perceptions of ease of use. Similarly, real-time system awareness and automated warning notifications could increase perceived usefulness. These beliefs can then influence confidence and behavioral intention with technology.

While this study does not statistically validate this causal chain, the descriptive results align with this theoretical relationship postulated in the methodology.

C. Role of Automation and Reduced Maintenance Effort

Maintenance effort was another factor deemed important. 36.7% of survey participants said that a significant decrease in maintenance effort on a day-to-day basis would affect their buying decision towards buying the system.

This metric came as a surprise to me as automation solutions are often judged solely on technical efficiency in agricultural research contexts. Household end users may place value on automation for reasons other than increased efficiency. Automation could be appreciated by users if it means they have to put less knowledge, attention, and time into keeping the system running.

The IoT system architecture proposed here should therefore not only be judged on if the sensors and actuators are operating correctly. It should also be considered if the sensors and automation are alleviating burden for the user in a meaningful way.

As such, the original goal of decreasing maintenance effort by ~60% should be considered a design goal instead of an experimentally validated finding at this time. Empirical testing of a prototype would be needed to measure how much time it actually takes to maintain a conventional setup versus an automated one.

D. Digital Lift in Purchase Intention

Just comparing the average scores of the conventional versus IoT-enabled aquaponics suggests Digital attributes may help drive market acceptance. 20.0% of respondents indicated the maximum purchase intention after viewing the IoT-enabled attributes, as compared to 13.3% for the baseline configuration.

While this difference is slight and should not be considered significant without running a paired test, it is noteworthy for purposes of exploration. Not only was the average higher, but the change moved in an intuitively favorable direction; it can be assumed that some consumers who were unsure about conventional aquaponics were swayed by the promise of easier monitoring/maintenance.

Such an observation can be used to help refine the role of Digitization within the system being proposed. The addition of IoT technology is not intended to simply create a high-tech version of aquaponics. Instead, the digital component could alleviate at least some of the ambiguity that discourages potential consumers from purchasing.

As such, Digital Lift can be kept as a working name for this phenomenon. However, it should be validated with a larger sample size and proper statistical tests.

E. Relevance to the Omani Context

Interestingly, results also identified factors that would have unique implications for implementation in Oman. The extreme temperatures in Omani summers were a concern for 40% of those surveyed for how it would impact the aquaponics-system functionality.

Climate conditions therefore provide additional support for the importance of continuous monitoring. Operating an aquaponics system in such high temperatures may create a need for up-to-date information on water temperatures and other environmental factors. Remote monitoring and automatic notifications would allow residential users to be more cognizant of shifting conditions without having to constantly monitor the system in person.

Another implication based on survey results is that familiarity with existing smart-home technology could influence perceptions of technology within agriculture. As 76.7% of respondents had some experience with smart-home technology, introducing an IoT enabled aquaponics system may be more effective if it was marketed as part of a smart-home system rather than an agriculture system.

This could be especially useful for residents in urban areas that want to live sustainably but may not have the time or knowledge to manage traditional farming practices.

F. Implications for System Design

Recommendations for system designers

A few recommendations for system designers can be taken from the results. Firstly, "less is more" should be taken into account as a design principle. Adding more sensors or technical capabilities will benefit the consumer little if the displayed information becomes difficult to comprehend as a result.

Secondly, measurement should be coupled with explanation. An associated mobile app should therefore explain what abnormal measurements mean and preferably provide recommended courses of action instead of merely presenting sensor values to the user.

Thirdly, Alerts should indicate how urgent a situation is without alarming users about inconsequential notifications.

Fourthly, automation should be implemented where it can assist users with rote tasks that are perceived to be difficult, repetitive, or

time-consuming. Automation features that address water quality monitoring, system maintenance reminders, or even fully automated adjustment mechanisms are therefore likely to have more practical benefits than technology that is added "just because."

Lastly, the Health Score feature should remain intelligible to users. People should be able to see what measurements affect the score and understand why a system is flagged as healthy or at risk. Transparency may prevent a biological black box from simply becoming a digital black box.

G. Study Limitations

There are several limitations to consider when interpreting the results. The study only had 30 respondents and utilized convenience sampling. Recruitment was also heavily skewed towards younger participants. For these reasons, the data cannot be considered perfectly representative of Oman's population.

The study measures stated purchase intention, not actual purchasing behaviour. A participant may answer questions positively to seem in agreement with proposed digital features but may not actually purchase or regularly use the system in real life.

Findings related to notifications, automation, and the Health Score were based on participants' perceptions of hypothetical functionality. Actual reductions in maintenance effort, improved stability, and increased user confidence can only be validated by prototype testing over an extended period of time.

Lastly, all percentages reported are descriptive statistics. The author does not have access to the respondent-level dataset and has not performed any statistical tests. As such, the results should not be discussed as if they are statistically significant correlations, causal effects, or regression coefficients.

The results still provide helpful insight into factors that influence purchase intention among potential consumers of IoT-enabled home aquaponics systems in Oman.

VI. CONCLUSION AND FUTURE WORK

The research attempted to determine if IoT based digital connectivity could enhance customer acceptance of home aquaponics systems in Oman. Emphasis was placed on the barrier of customers perceiving aquaponics to be too complex for them and whether system monitoring, system automation, streamlined information, and mobile accessibility increased customers' sense of ease and comfort with the idea of adopting aquaponics. Researchers discovered that consumers see several hurdles before they would feel comfortable buying into traditional aquaponics. 60% of those surveyed were worried about not knowing there was a problem with their system soon enough to correct the issue. Another 53.3% viewed testing water-chemistry by hand as too difficult or time consuming. Climate was also an issue for 40% of users who viewed extreme summer temperatures in Oman as a risk factor.

These results lead into the papers thesis that one of the barriers to consumer acceptance of home aquaponics is the ability to see what is going on. Customers understand the advantages of aquaponics in terms of sustainability but may not know if they will be able to successfully care for the living ecosystem within their tanks. This paper refers to this as the biological black box.

Consumer receptivity was also seen towards several aspects of proposed digital features. Over half of participants (56.7%) expressed that they would be less concerned about failure if real-time notifications were made available on their mobile device. Simplified Health Score dashboard was favorably viewed by 40% of participants, and 43.3% expressed increased likelihood to farm at home if digital guidance was available.

Purchase intention was also compared between the conventional system and IoT-enabled system. There was a higher percentage of participants that answered very likely (13.3% vs 20.0%) when digital features were added to the system. While statistical testing is needed to make any conclusions about significance, this increase provides an initial indication that digital features could enhance the perceived value of home aquaponics to consumers.

A. Contributions of the Study

The study makes several contributions.

To begin, the current study moves the conversation around smart-agriculture technology away from its current focus on technical applications and towards the end-user experience of these biological technologies. Rather than benchmarking successful IoT integration by sensor precision or the performance of automation subsystems, this study asks if digital technology can simplify aquaponics for novice operators.

Second, this work adds the idea of a biological black box to describe the consumer uncertainty that surrounds complex biological processes. This adds to the conversation by illustrating how barriers to adoption can stem from more than fiscal or technological limitations; they can also be created by a user's inability to know what is happening inside the system.

Third, this study suggests the Health Score as a method for consolidating multivariate environmental readings into easy-to-understand information. Coupled with real-time alerts and digital instruction, this study begins to pave a user-centred path for future smart-aquaponics interface design.

Fourth, this study offers the idea of Digital Lift to quantify the increase in consumer purchase intent that occurred with the introduction of IoT functionality. While this concept needs further statistical investigation, it lays the groundwork for future exploration into how digital features affect consumer acceptance of sustainable domestic technology.

Finally, this work provides novel insight on domestic aquaponics adoption within the context of Oman. The results of this study highlight that technologies designed for implementation in Oman should consider high ambient temperatures, user time constraints, varying levels of agricultural knowledge, and increased comfort with smart-home technology.

B. Practical Implications

Pragmatically speaking, we feel that our results suggest that a perfect smart-aquaponics platform should not attempt to be too smart itself.

Rather, we feel that the platform should focus on bridging consistent environmental sensing with a portal capable of turning dense measurements into simple, actionable information. Users should be made aware of these shifts in real-time and if unfavorable changes to their system are detected, the portal can provide directions to help return their system to optimal conditions.

Automated processes can be implemented depending on the manual labor or technical expertise necessary to complete the task. The integration of all three of these features has the potential to push home aquaponics past the niche gardening community and into the mainstream as an easy-to-use smart home device.

Not only would this create more enthusiasts of at-home food production, but it could help to accomplish worldwide goals of water conservation, digitization, and hyper-local farming.

C. Future Work

Several directions are recommended for future research.

First, the study should be extended to a substantially larger and more diverse sample representing different age groups, governorates, educational backgrounds, and levels of agricultural experience across Oman.

Second, the proposed IoT-enabled aquaponics platform should be implemented as a functioning prototype and evaluated under real operating conditions. Future experiments should measure objective indicators such as maintenance time, water-quality stability, alert response time, sensor reliability, and system availability.

Third, longitudinal user studies would be valuable for determining whether initial positive attitudes toward the Health Score, automation, and mobile notifications remain stable after prolonged system use.

Fourth, future analysis should incorporate appropriate inferential statistics. Where the same participants evaluate conventional and IoT-enabled alternatives, paired statistical tests can be used to determine whether differences in confidence and purchase

intention are statistically significant. Relationships among perceived complexity, ease of use, confidence, and purchase intention can also be investigated using correlation or regression methods with an adequately sized sample.

Finally, future work could investigate additional intelligent functions, including predictive anomaly detection, adaptive recommendations, automated environmental control, and personalized maintenance guidance. Such developments could further shift aquaponics from a system requiring specialist knowledge toward an accessible and intelligent household sustainability technology.

In conclusion, the study suggests that digital integration may help bridge the gap between the environmental potential of aquaponics and the practical confidence required for household adoption. IoT technology alone is not sufficient; its value depends on whether complex biological information can be transformed into clear, timely, and actionable support for users. By placing transparency, usability, and consumer confidence at the centre of system design, smart aquaponics may offer a more practical pathway toward sustainable home-based food production in Oman.

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Real Time Parking Monitoring System for a University Campus: A User-Centered and Camera-Based Smart Mobility Framework

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ABSTRACT

Finding parking spaces can prolong search time, encourage unnecessary driving around, waste fuel and reduce satisfaction amongst users. In this study, parking issues at University of Technology and Applied Sciences (UTAS)–Al Mussanah were explored, and framework requirements for real-time parking space finding system grounded in the local context are proposed. Design-based mixed methods were used including a review of smart parking systems, investigation of campus needs, and survey of 64 valid participants consisting of students and staff. Descriptive and inferential statistics characterized parking experience, perceived usefulness, desired features, technology-access, and privacy concerns. Peak parking search times were in the morning and most respondents reported difficulties finding parking. Perceived parking satisfaction with the current state (M=2.41/5) was low, but perceived usefulness of a real-time space finding system was greater (M=3.84/5). Having a live map showed with available spaces was the most popular desired feature (84.4%), followed by reservation/booking capability (56.3%), and push notifications when a space is available (53.1%). Most students reported having access to a smartphone app (95.3%), and only 23.4% reported mobile Internet was "never" or " Rarely" dependable. Spearman's correlation found a significant positive relationship between parking search time and perceived usefulness ($r_s=0.41$, $p=0.003$). Participants that spent less time searching for parking were more likely to be satisfied with parking ($r_s=-0.68$, $p<0.001$). Grounded in the survey findings and literature review, a scalable camera-only architecture is proposed consisting of computer vision, edge/IoT processing, backend service, and mobile-first web frontend. This research aims to provide an evidence-based guide for future development and real-world testing of smart university parking systems in Oman.

Keywords - Smart parking, real-time parking, computer vision, IoT, smart campus, parking guidance, campus mobility.

INTRODUCTION

Parking availability is both an operations and mobility challenge at universities with dense, class-schedule-oriented vehicle demand. Current parking practices at UTAS–Al Mussanah offer little real-time information as to space availability. As such, drivers may search through parking areas for open spaces - often doing so during morning peak times. Searching for parking can lead to increased congestion, travel distance on campus, excess fuel consumption, and overall user frustration.

The core issue to be addressed by this work is the lack of timely information about the availability and location of existing spaces, rather than the lack of physical spaces themselves. Smart parking systems can overcome this barrier by providing sensing, data processing, and user guidance in tandem. Techniques range from ultrasonic sensors [1], RFID systems [2], cloud-connected IoT devices [3], computer vision [4], edge computing [5], [6], to intelligent parking guidance logic [7]–[9]. While these provide options for sensing and processing, reported systems often focus on simulations [1], [5], [6], [8], small-scale deployments [2], [3], [7], rely on cloud services [2]–[5], [7], or focus on urban traffic flow [1], [4], [9].

Filling this gap, this work scopes the problem within UTAS–Al Mussanah and investigates three key questions: 1) How detrimental are current parking conditions to users on campus? 2) What capabilities can users expect from a real-time parking system? and 3) What system architecture can support real-time occupancy information while balancing scalability, cost, connectivity, and privacy?

Contributions of this work include: (1) a data-driven understanding of parking experiences and user needs at UTAS–Al Mussanah; (2) a survey of technological solutions which can operate in bandwidth and scale constrained campus environments; (3) a high-level design of a camera-based, privacy-sensitive smart parking architecture; and (4) a list of implementation and testing requirements to be used for future prototype development.

II. RELATED WORK

Smart parking solutions have historically evolved from occupancy-sensing technology to broader sensing, communication, analytics, and guidance systems. While Idris et al. [1] provide a taxonomy for smart parking systems spanning guidance, transit-based, smart payment, electronic parking, and automated parking solutions from a technological perspective, Yan et al. [2] approached sensor-based secure parking through wireless communications and cryptographic methods. The need for security in connected systems has become especially relevant. Sensor-centric solutions are desirable for their simplicity. Khanna and Anand [3] provided implementation details for an IoT-based prototype using Raspberry Pi as the

sensing and communication platform with ultrasonic sensors, Wi- Fi, and cloud connectivity. Mittal et al. [4] presented a low-cost parking monitoring system using Arduino, RFID tags, GPS trackers, and ultrasonic sensors. Their simulation results validate that offline availability can be detected with such systems. Sensor-centric solutions provide inexpensive methods for reducing price points on deployed infrastructure.

However, challenges may arise when scaling up to support massive numbers of sensors and maintaining hardware deployed across large outdoor areas. Cloud-connected solutions provide a centralized point for monitoring and remote access. Elfaki et al. [5] discussed a system that uses IoT sensing devices with RFID tags and optical character recognition along with cloud-connected platforms for automated monitoring and control of parking. Their results show how such integrated sensing can work in practice, but reliance on cloud endpoints can create latency issues and connectivity bottlenecks. An extension of cloud computing, known as edge computing, provides an alternative framework by processing information on edge devices. Edge devices sit between sensors and the cloud. Kim et al. [6] present an efficient, resource-aware approach for real-time monitoring with an edge device and single-shot detector (SSD)MobileNetV2-based detector. The authors show that computation can be offloaded to the edge with minimal sacrifice to detection accuracy. Computer vision holds promise in this area because cameras can cover multiple spaces at once and allow software-defined reconfigurations of parking environments.

Nguyen and Sartipi [7] explore automatic parking-space detection and status identification with Deformable DETR reporting accurate detection with zero manual labeling. Related work has considered systems for parking enforcement such as the camera- and sensor-based system discussed by Almawgani et al. [8]. Wu et al. [9] discussed information-sharing parking guidance policies through Bayesian modeling. Their work illustrates the potential benefits of improved occupancy estimation and guidance policy. Another concern with camera-based systems is privacy.

While Al Amiri et al. [10] discuss a privacy-preserving smart parking architecture using blockchain and private information retrieval systems, these methods may require additional complexity. With respect to privacy on university campuses, a smart parking architecture should limit the collection of personally identifiable information (PII). For example, video streams of parking lots should only process the features necessary to detect parking occupancy. Motivated by these considerations, the literature leaves an opportunity for contextually appropriate smart parking architectures on university campuses. The current study aims to bridge this gap through a discussion of user needs coupled with a proposed camera-based architecture for real-time parking availability that considers mobile usability, privacy, and connectivity resilience.

III. RESEARCH METHODOLOGY

A. Research Design

Exploratory research/design was employed. The approach taken was design-driven. It consisted of performing a targeted literature review coupled with a description of the UTAS–Al Mussanah parking problem and followed by conducting a user survey. Requirements definition and discovery of an achievable architecture were goals instead of claiming operationally measured performance of a deployed system.

B. Participants and Instrument

Population consisted of students and staff who drive to campus and park at the University. Purposive sampling was employed to invite students who park on campus to participate based on their experiences. After cleaning the data there were 64 valid respondents (61 students (95.3%) and 3 staff members (4.7%). The survey consisted of questions about demographics, current parking experiences, perceived usefulness of a real time system, feature preferences, Internet availability and privacy concerns. Questions using a Likert scale were answered using five response options when relevant.

C. Data Processing and Analysis

Errors were removed from survey data, addressing incomplete (missing), inconsistent, duplicate, and anomalous responses. Values of categorical variables were standardized. Frequencies, percentages, means, medians, standard deviations, variance, and skew were calculated for descriptive purposes. Percent frequencies of selection were calculated for multiple-response items. Spearman's rank correlation coefficients were calculated for variables associated with ordinal parking- time, usefulness, and satisfaction questions. Although a one-sample t-test is also reported in the original article comparing results against a two-minute reference value, because this reference was intended to represent a design guideline rather than a universally agreed upon engineering standard, we interpret this result as demonstrating that reported search times were greater than the threshold selected for this study rather than as demonstrating evidence against some external standard.

D. Proposed System Architecture

This reference architecture is composed of four logical layers. The sensing layer performs imaging of parking areas using carefully-positioned cameras. The edge/processing layer completes computer-vision inference to identify parking-spaces as either occupied or available, and may transmit only occupancy-data when possible. The application/backend layer correlates parking-space availability, timestamps, location identifiers for parking areas, and optionally navigation info. Lastly, the user-interface layer will serve a mobile-first web-application (or similar UI) with real-time availability, navigation and any other desired services selected by the user.

Capturing personal-identifiable information about devices (or individuals) should be avoided to enable privacy- by-design compliance. Cameras should be angled to monitor parking-space occupancy instead of recognizing individuals; unnecessary recording of video should be avoided; and, when processing images is necessary, consider edge-processing and automatic anonymization of those images. Due to 23.4% of respondents identifying unreliable internet access, local caching, resilient-sync capabilities, and fallback information should be considered.

IV. RESULTS

A.Respondent Profile and Arrival Patterns

In terms of who was included in the sample, students made up 95.3% of it (n=61), while staff accounted for 4.7% of it (n=3). Respondents who identified as male made up 67.2% (n=43), while those who identified as female made up 32.8% (n=21). Most participants had arrived before noon: 50.0% of respondents (n=32) arrived between the hours of 8:00 and 10:00 AM. Another 37.5% (n=24) arrived before 8:00 AM. Only 1.6% (n=1) of respondents arrived after noon. This gathers valuable information on when users arrive at KU, determining that the morning is a key time period for future tests of the system.

B.Parking Search Time

Search time was highly skewed. About 15.6% (n=10) reported less than 2 minutes, 32.8% (n=21) took 2–5 minutes, 26.6% (n=17) took 6–10 minutes, 20.3% (n=13) took 11–20 minutes, and 14.1% (n=9) took more than 20 minutes to find a parking space. With category midpoints imputed, the calculated mean search time was 7.66 minutes; the median search time was 3.5 minutes with standard deviation 6.82 minutes. Positive skewness (1.22) reflects longer search times experienced by a minority of subjects.

C. Satisfaction and Perceived Usefulness

Participants were generally dissatisfied with their current parking experience (mean=2.41/5; median=2; mode=1; 39.1% very dissatisfied (n=25), 20.3% dissatisfied (n=13), 23.4% neutral (n=15), 10.9% satisfied (n=7), 6.3% very satisfied (n=4)). The perceived usefulness of a real-time parking system was higher (mean=3.84/5; median=4; mode=5). Of participants, 35.9% believed the proposed system would be extremely useful and 26.6% thought it would be very useful.

D. Preferred System Features

The live map indicating available parking spaces was the most popular feature (84.4%, n=54). Parking reservation/booking came in second (56.3%, n=36), followed by receiving a notification when a spot becomes available (53.1%, n=34), estimated time to walk to the parking spot from (50.0%, n=32), navigation/directions to (46.9%, n=30), and details about restricted parking spots (18.8%, n=12). This supports developing a user interface focusing on visual representations of availability and quick decision making assistance.

E. Access, Connectivity, and Privacy

Smartphones (95.3%, n=61) were the most commonly used access device (tablet computers 3.1%, n=2, laptops 1.6%, n=1). Cellular Internet connections were reported as always reliable by 39.1% (n=25), mostly reliable by 37.5% (n=24), sometimes reliable by 12.5% (n=8), and 10.9% (n=7) reported connections that were unavailable. In other words, 23.4% of participants did not report having consistently reliable cellular connectivity. Mean concern for privacy was 2.52 out of 5; 35.9% reported being not at all concerned while 12.5% reported being extremely concerned about privacy. Privacy and connectivity were therefore taken as explicit requirements instead of orthogonal threats.

F. Inferential Findings

The one-sample t-test of parking time compared to the study benchmark of less than two minutes posted $t = 12.14$, $p<.001$. Using Spearman's rho, a positive correlation was found between search time and perceived usefulness of the proposed system ($r_s=.41$, $p=.003$), meaning that subjects who reported longer search times also reported higher usefulness. A negative correlation existed between search time and reported satisfaction with current system ($r_s=-.68$, $p<.001$), meaning that subjects who reported longer search times reported less satisfaction. Note that these are correlations using survey responses and are not necessarily causal evidence that installing the system will lead to a specific decrease in search time.

TABLE I: SUMMARY OF KEY SURVEY FINDINGS

Measure	Result	Interpretation
Current parking satisfaction	M=2.41/5	Low satisfaction
Perceived usefulness	M=3.84/5	Generally positive
Live availability map	84.4%	Most requested feature
Reservation/booking	56.3%	Second-highest feature
Spot-availability notifications	53.1%	Important alert function
Smartphone access	95.3%	Mobile-first interface needed
Inconsistent Internet	23.4%	Connectivity resilience needed
Search time vs. usefulness	$r_s=0.41$, $p=0.003$	Positive association
Search time vs. satisfaction	$r_s=-0.68$, $p<0.001$	Negative association

V. DISCUSSION

The survey data support feasibility in several ways. First, report rates suggest that parking information represents a legitimate usability problem in the study context. The clustering of arrivals before 10: 00 AM also aligns with when parking demand would be expected to be most clustered. The right-skewed search time distribution suggests heterogeneity in the problem: although many respondents report quickly finding parking, there are enough respondents who experience elongated searches to warrant consideration. This further supports mitigating uncertainty about where vacant spaces are located with real-time information.

Second, the difference between current satisfaction (M=2.41) and perceived usefulness of the proposed real-time system (M=3.84) suggests participants made a distinction between dissatisfaction with searching under current conditions and expected satisfaction with a technology-enabled alternative. Finally, interest in a live availability map was the strongest preference, which is highly relevant to system design. Whereas other functions rely on users having parked or having found a space, a map can provide information prior to entering or circulating in a parking area. Reservation and notification functions can be thought of as value-added services that complement the core occupancy- information capability.

On the technical side, the camera-based approach is in line with literature trends toward computer vision and edge processing [6], [7]. Cameras may help reduce the total number of physical devices needed and allow for changes to parking-space definitions without making additional hardware adjustments. Although computer vision has performed well in controlled experiments, its effectiveness is highly dependent on camera placement, illumination, occlusion, weather, and scene variability. It will be important to validate the architecture using conditions representative of outdoor parking facilities before being deployed operationally.

Autonomy also creates contextual constraints. About one-quarter of respondents said they did not always experience reliable mobile Internet. This suggests the architecture should be designed so occupancy processing can occur locally if cloud connectivity is unavailable, and information can be synchronized when connection is restored. Privacy should be treated in a similar manner – at the architecture level. A parking occupancy system should be designed to detect occupancy, limit retention of raw imagery, and not collect personally identifying information unless there is a specific operational need and corresponding governance framework.

Lastly, it is important to note that survey results cannot be used to demonstrate the proposed system will actually lead to reductions in parking search time. The system was not deployed; respondents could not directly comment on its ease-of-use or usefulness. The observed positive relationship between search time and perceived usefulness suggests the proposed intervention is relevant to address. The negative relationship between search time and satisfaction with the current parking process indicates search has bearing on user experience. Reductions in search time, cruising distance, fuel use, and emissions can only be credibly measured using controlled field experiments after implementation.

VI. PROPOSED IMPLEMENTATION FRAMEWORK

Rollout would likely be phased: Phase 1 would involve scanning and mapping existing primary parking areas, determining camera FOVs, and specifying privacy/data-governance concerns. Phase 2 would require building a small-scale minimum viable prototype around selected camera feeds and a CV model that performs occupancy classification. Phase 3 would connect occupancy output to backend services and a mobile-first user experience. Phase 4 would involve closed beta field-testing during peak and off-peak hours. Phase 5 would assess scalability and integration with other mobility services on campus.

Core metrics would include: parking-space detection precision, recall, and F1-score; end-to-end data latency; availability-state accuracy as a function of time; average search time for parking; distance cruised; user satisfaction; network/system availability; computation/power requirements. Privacy metrics should measure duration of unnecessary image capture and ability of the system to function without the ability to identify specific users. These metrics would expand upon the current study and deliver an experimentally validated smart-campus solution.

VII. LIMITATIONS

The following limitations apply to this study: First, we implemented purposive sampling with a small sample size (n = 64 valid responses) and should not generalize findings to all UTAS users until a random sample of the population has been collected and assessed. Second, we collected self-reported parking experiences and perceptions instead of behavioral measures from the system itself. Third, we did not physically implement our computer vision architecture; accuracy during daylight, inclement weather, vehicle occlusion, and rush hours should be assessed. Fourth, we only analyzed parking behaviors on one university campus. Different campuses may have varying physical layouts, traffic patterns, and technology limitations.

The paper mentions 62 Participants in previous sections and the results add up to 64 responses. We use 64 in this paper as our analytical sample size because the demographics and response frequencies consistently add up to that number. Prior to journal or conference submission, the authors should confirm with the original survey export and use that value instead if the raw dataset determines a different sample was finalized.

VIII. CONCLUSION

This paper surveyed parking conditions at UTAS–Al Mussanah, as well as garnering user requirements for a real-time parking guidance system. The results indicate morning peak arrivals are clustered, parking search time variance is high, satisfaction with the current parking system is low, and perceived usefulness of a real-time system is moderately high. Respondents chose a live occupancy map as their preferred feature by wide margin, and overwhelmingly selected smartphones as their preferred method of accessing the system.

Finally, connectivity and privacy were noted as key contextual concerns. The paper proposes a resultant camera-based architecture to fit these needs. Integrating computer vision, edge/IoT computation, backend services, and a mobile-first frontend, the architecture aims to deliver realtime occupancy information with less reliance on per-space sensors and greater capacity for privacy-sensitive processing. While the paper presents user demands and a corresponding technical design philosophy, real-world measurement of the system effectiveness has been left as future work. The authors should look to build at least a minimum viable prototype and test it in a campus environment with objective performance, usability, connectivity, and privacy measurements.

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