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Dedication

It is our pleasure and great privilege to present the 78th issue of the Academic Journal of Research and Scientific Publishing to all researchers and professor who published their research in the issue, and we thank and appreciate to all contributors and supporters of the academic journal and those involved in the production of this scientific knowledge edifice.

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Context-Aware Face Presentation Attack Detection (A Dual-Branch Convolutional Neural Network)

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Abstract

Face recognition systems are susceptible to presentation attacks, which can severely compromise their reliability in security-sensitive applications. Existing methods, such as Deep Pixel-wise Binary Supervision (DeepPixBis), primarily focus on facial regions, often neglecting critical contextual cues in the surrounding image that could signal spoofing attempts. This paper introduces an efficient dual-branch convolutional neural network architecture that integrates facial and contextual information for robust face presentation attack detection, all while maintaining a compact model size. The proposed model processes the extracted face and the entire image independently, producing a pixel-wise map for the face and a binary output for the full image. Trained and evaluated on the OULU-NPU dataset using standard ISO/IEC 30107-3 metrics, the proposed approach achieves state-of-the-art performance among DeepPixBis-based models in protocols II and III. Additionally, it demonstrates state-of-the-art performance in protocol II across all existing models, not just those based on DeepPixBis. Remarkably, it achieves this while being the smallest model among all existing anti-spoofing deep-learning models (1.4M parameters), demonstrating its practicality in real-world scenarios.

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1. Introduction

Face recognition is now a ubiquitous biometric technology, widely adopted in applications from mobile authentication to industrial security due to its convenience. However, this success has created a critical vulnerability: presentation attacks (PAs), or spoofing. Attackers can compromise authentication integrity using simple artifacts like printed photos, video replays, or 3D masks. In high-security settings, such failures can lead to significant breaches, making robust Presentation Attack Detection (PAD) an essential safeguard.

Early PAD research relied on hand-crafted features to detect specific spoof artifacts. This included texture analysis using Local Binary Patterns (LBP) (Määttä et al., 2011), motion analysis (Anjos & Marcel, 2011), and liveness cues like eye blinking (Pan et al., 2007). However, these traditional methods often failed to generalize to new attack types and environments. The adoption of deep learning, especially Convolutional Neural Networks (CNNs), marked a paradigm shift by enabling models to automatically learn robust, discriminative features from raw pixel data, significantly improving performance.

Despite the success of deep learning, a significant limitation persists in many state-of-the-art models: an over-reliance on the facial region while neglecting the rich contextual information present in the entire scene. These models often operate solely on tightly cropped face images, discarding valuable cues that could signal a presentation attack. For example, the edges of a handheld screen, reflections from a printed photo, or unnatural lighting inconsistencies in the background can be strong indicators of a spoof, as illustrated in Figure 1. Ignoring these contextual cues can limit the effectiveness of PAD systems, particularly against sophisticated or novel attack vectors.

To address this limitation, this paper introduces an efficient dual-branch context-aware neural network, named "Dual-PADNet." Building upon the Deep Pixel-Wise Binary Supervision framework, the primary aims of this research are to: (1) propose a novel dual-branch architecture that simultaneously processes facial and contextual information to improve detection accuracy without increasing model size; (2) demonstrate that high performance can be achieved with an efficient training strategy and an exceptionally compact model; and (3) validate the model's effectiveness on the OULU-NPU benchmark dataset, aiming for state-of-the-art performance. The rest of this paper is organized as follows: Section 2 reviews related work, Section 3 addresses the research gap and our contributions, Section 4 details our proposed methodology, Section 5 presents experimental results, Section 6 discusses the findings, and Section 7 concludes the paper with suggestions for future work.

Figure 1: Looking at the face only, it is extremely difficult to determine whether the image is a spoof or not. However, when examining the full image, many artifacts show up such as the colors in the bottom-left, bottom-right, and top-right that might be caused by a reflection.

2. Related Work

The field of Presentation Attack Detection (PAD) has evolved significantly, transitioning from methods based on hand-crafted features to sophisticated deep learning architectures. This section reviews this progression and identifies the key challenges that motivate the present study.

2.1. Traditional Hand-Crafted Feature Approaches

Early efforts in PAD focused on identifying specific, pre-defined artifacts associated with spoofing attacks. These methods can be broadly categorized by the cues they analyze. Texture-based methods were among the most prominent, leveraging descriptors to capture subtle patterns that differentiate live skin from artificial materials like paper or screens. For example, Määttä et al. (2011) employed Local Binary Patterns (LBP) to analyze micro-textures, while Boulkenafet et al. (2016) extended this concept using color texture analysis. Concurrently, motion-based methods exploited temporal information, assuming that the subtle, involuntary movements of a live person differ from the static nature of a photo or the predictable motion of a video replay (Anjos & Marcel, 2011).

A third category, liveness-based methods, sought physiological signs of life, such as eye blinking (Pan et al., 2007). While foundational, these traditional approaches often struggled with generalization, as their hand-crafted features were typically sensitive to variations in lighting, environment, and attack types not seen during development.

2.2. The Shift to Deep Learning Architectures

The limitations of traditional methods paved the way for deep learning, particularly Convolutional Neural Networks (CNNs), which can automatically learn hierarchical and highly discriminative features from data. This paradigm shift led to a significant leap in performance. A foundational work in this area is Deep Pixel-wise Binary Supervision (DeepPixBis) by George and Marcel (2019), which proposed supervising the network at a pixel level. By training the model to generate a binary map distinguishing live and spoof regions, DeepPixBis encouraged the network to learn fine-grained spoofing artifacts. Other deep learning strategies have also been explored. For example, Liu et al. (2018) introduced a CNN-RNN model that incorporated auxiliary supervision using depth maps, while Atoum et al. (2017) proposed a two-stream CNN that fused information from image patches and estimated depth.

2.3. Enhancements to DeepPixBis

Building on the success of initial deep learning models, subsequent research has focused on refining architectures and loss functions. Hossain et al. (2020) proposed A-DeepPixBis, an enhancement to the DeepPixBis framework. They introduced an angular margin-based binary cross-entropy loss (A-BCE) to improve feature discriminability and incorporated an attention mechanism to guide the model toward more informative facial regions. These improvements led to more robust performance, particularly in challenging cross-dataset scenarios. Such works highlight a trend toward not just deeper or wider networks, but smarter supervision and architectural design to extract more meaningful anti-spoofing features.

2.4. Current Challenges

Despite these advancements, several critical challenges remain in the field of face PAD, defining the research gaps that current work aims to address:

- **Neglect of Contextual Information:** Many of the existing methods, including sophisticated deep learning models, operate on tightly cropped face images. This approach inherently discards the surrounding scene, which may contain crucial evidence of an attack, such as the borders of a tablet, reflections on a printed photograph, or unnatural background elements.

- **Poor Generalization to Unseen Attacks:** Many models exhibit a significant drop in performance when evaluated on new attack types, camera sensors, or environmental conditions that were not part of their training data. Indicating a need for models that learn more fundamental and generalizable features of presentation attacks.
- **Model Size**: While most models used on this field are relatively small, their computational cost can sometimes be prohibitive for real-world deployment on resource-constrained platforms, such as mobile devices or embedded systems. There is a persistent need for lightweight models that do not sacrifice performance.

3. Research Gap and Contributions

The literature review reveals a clear research gap: a lack of PAD models that effectively leverage contextual information while remaining computationally efficient. Existing methods are predominantly face-centric, making them blind to obvious spoofing cues in the surrounding scene. Furthermore, smaller high-performing models are desired considering the deployment of facial recognition on edge devices. This paper directly addresses these limitations by proposing a model designed to be both context-aware and lightweight.

Our contributions are as follows:

- **Novel Dual-Branch Architecture**: We introduce a dual-branch network that simultaneously processes facial and contextual information, enhancing the model's ability to detect presentation attacks while achieving a state-of-the-art compact model size.
- **Efficient Training Strategy**: We only use 5 uniformly sampled frames per training video, 5 uniformly sampled frames per validation video, and train for 30 epochs. Along with one augmentation per image, we believe this reduces overfitting and computational costs without compromising performance significantly.
- **State-of-the-Art Model Size**: Previous research used DenseNet-161 (Huang et al., 2017), Bi-FBN (Roy et al., 2021), and CDCN (Yu et al., 2020). All of these are bigger than the model used here, which is the first 8 layers of DenseNet-121 amounting to only 1.4 million parameters.

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- **State-of-the-Art Performance**: Our model achieves competitive results across all protocols of the OULU-NPU (Boulkenafet et al., 2017) dataset, as per ISO/IEC 30107-3 metrics (International Organization for Standardization, 2017). Particularly, it is the best model for protocols II and III among DeepPixBis-based models, and the best model for protocol II among all anti-spoofing models. See section 5.1 for protocol definitions and tables 1 & 2 for comparison with other models.

4. Methodology:

4.1. Overview:

Our proposed method addresses the limitations of existing approaches by incorporating contextual information through a dual-branch architecture. One branch processes the extracted and aligned face, while the other processes the entire image. This design allows the model to capture both facial features and contextual clues indicative of presentation attacks. The architecture is shown in figure 2.

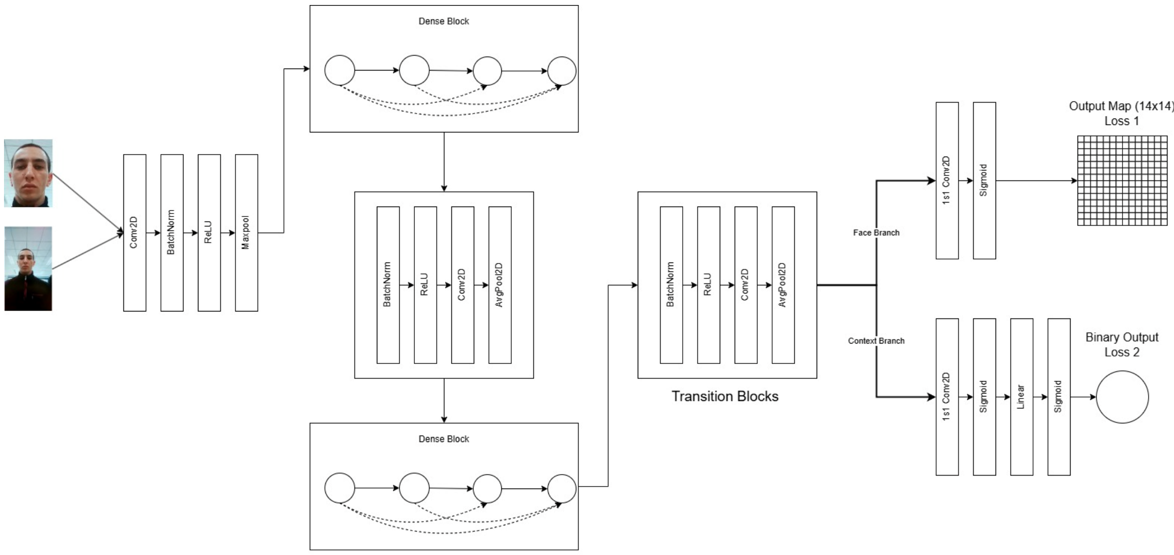

Figure 2: The extracted face and context image (full image) share the same weights for the first 8 layers of Densenet-121. Afterwards, the face branch outputs the pixel map, and the context branch outputs the binary input.

4.2. Data Preprocessing:

4.2.1. Face Extraction and Alignment

We utilize RetinaFace (Deng et al., 2020), a robust face detection and alignment method, to extract and align faces from images. RetinaFace (Deng et al., 2020) detects facial landmarks and aligns faces to a canonical orientation, ensuring consistency across inputs. The extracted face & aligned face is padded by 25% to ensure no parts of the face are left.

4.2.2. Data Augmentation

To enhance the model's generalization capabilities, we apply various data augmentation techniques:

- Random Horizontal Flips: Flipping images horizontally with a 50% probability.
- Random Affine Transformations: Applying random rotations (±15 degrees) and scaling (90%-110%).
- Color Jitter: Randomly adjusting brightness, contrast, and saturation (±20%).

One augmentation is done per frame.

4.3. Dual-Branch Network Architecture:

Our model consists of two branches: the Face Branch and the Context Branch.

4.3.1 Face Branch:

The Face Branch processes the extracted face image and generates a 14×14 pixel-wise map indicating the likelihood of each pixel being part of a bona fide face.

- Backbone Network: We use a DenseNet-121 architecture (Huang et al., 2017) pre-trained on ImageNet for feature extraction.
- Encoder: The encoder consists of the first eight layers of DenseNet-121 (Huang et al., 2017), capturing hierarchical facial features.
- Decoder: A 256×1 convolutional layer reduces the feature map to a single-channel pixel-wise map.
- Activation: A sigmoid function is applied to produce probabilities between 0 and 1.

4.3.2. Context Branch:

The Context Branch processes the full image, capturing contextual cues that may indicate spoofing, such as background inconsistencies or artifacts.

- Shared Encoder: The Context Branch shares the same encoder architecture as the Face Branch, ensuring consistency and reducing the number of parameters.

- Decoder and Classification: Similar to the Face Branch, it uses a decoder followed by a fully connected layer to produce a binary output indicating spoof or bona fide.

The code for the model architecture can be found in our GitHub repository (Bahatheq, 2024).

4.3.3. Fusion and Decision Making

During inference, the outputs of both branches are combined to make the final decision.

- **Score Averaging**:

$$binary_{preds} = \frac{binary_{output} + scores}{2} \geq 0.5$$

Where $binary_{output}$ is the output from the Context Branch and *scores* is the mean of the pixel-wise map from the Face Branch.

4.4. Loss Function:

We employ a combined loss function that balances pixel-wise supervision and overall binary classification.

4.4.1. Pixel-Wise Binary Cross-Entropy Loss

The pixel-wise loss encourages the model to make accurate predictions at the pixel level for the Face Branch.

$$L_{\text{pixel}} = \frac{-1}{N}\sum_{i=1}^{N}[y_i log\,(p_i) + (1 - y_i) log\,(1 - p_i)]$$

Where N is the number of pixels, y_i is the ground truth label (0 for spoof, 1 for bona fide), and p_i is the predicted probability.

4.4.2. Binary Cross-Entropy Loss

The binary loss penalizes incorrect overall predictions from the Context Branch.

$$L_{\text{binary}} = -[y log\,(p) + (1 - y) log\,(1 - p)]$$

4.4.3. Combined Loss Function

We combine the two losses using a weighting factor λ=0.5:

$$L = \lambda L_{\text{pixel}} + (1 - \lambda) L_{\text{binary}}$$

4.5. Training Strategy:

4.5.1. Frame Selection:

To reduce overfitting and computational costs, we select 5 uniformly sampled frames from each video for training and validation. This approach ensures diversity in training data while maintaining efficiency. This also demonstrates the ability to use less training data and get sufficient results. Moreover, one augmentation for each sampled frame is added. However, when testing, 20 uniformly sampled frames are taken from each video. This is done to ensure that the testing is comparable to that of other research.

4.5.2 Optimization

- Optimizer: Adam
- Learning Rate: 1×10^{-4}
- Weight Decay: 1×10^{-5}
- Batch Size: 32
- Epochs: 30

4.6. Implementation Details:

- Hardware: Training and testing were conducted on NVIDIA GPUs with CUDA acceleration.
- Software: Implemented using PyTorch (Paszke et al., 2019).
- Reproducibility: All model configurations are documented for reproducibility.

5. Experiments and Results:

5.1. Dataset:

We trained and evaluated our model on the OULU-NPU dataset, a widely used and challenging benchmark for face PAD. The database was specifically designed to evaluate the generalization of PAD methods in mobile authentication scenarios and consists of 5,940 videos recorded from 55 subjects using high-resolution frontal cameras of six different smartphones in three different environments (mainly illumination and background scene). The attack types are limited to Printed Photo Attacks (created using two different high-quality printers) and Video Replay

Attacks (replayed on two different high-resolution displays). The dataset is organized into four rigorous protocols designed to test model robustness against specific variations:

- **Protocol 1:** Unseen environmental conditions (lighting and background).
- **Protocol 2:** Unseen Presentation Attack Instruments (PAIs).
- **Protocol 3:** Unseen camera sensors.
- **Protocol 4:** A combination of all three unseen conditions.

The choice of the OULU-NPU dataset over newer alternatives like CelebA-Spoof or CASIA-SURF was deliberate. Primarily, it serves as the standard evaluation benchmark for the foundational DeepPixBis and A-DeepPixBis models, against which our work is compared. Using the same dataset and protocols ensures a direct and fair comparison, accurately measuring the incremental improvements of our proposed architecture. Furthermore, the protocol design of OULU-NPU provides a robust framework for assessing a model's ability to generalize, which is a core focus of our research.

5.2. Evaluation Metrics

We use the ISO/IEC 30107-3 standard metrics (International Organization for Standardization, 2017):

- Attack Presentation Classification Error Rate (APCER): The rate at which attack presentations are incorrectly classified as bona fide.
- Bona Fide Presentation Classification Error Rate (BPCER): The rate at which bona fide presentations are incorrectly classified as attacks.
- Average Classification Error Rate (ACER): Represents the average of the APCER and BPCER, providing a consolidated performance metric.

$$ACER = \frac{APCER + BPCER}{2}$$

For all three metrics, a lower value indicates better performance with 0 being the perfect value.

5.3. Experimental Setup:

5.3.1. Training and Validation:

- Data Splits: Followed the standard splits provided in the OULU-NPU (Boulkenafet et al., 2017) dataset for fair comparison.

- Data Augmentation: Applied as described in Section 4.2.2.
- Best epoch criteria: the model with the lowest ACER is chosen as the final model.

5.3.2. Testing:

- Frame Usage: 20 uniformly sampled frames from each video are used during testing to ensure comparability with existing methods.

5.4 Results:

To assess the performance of our proposed Dual-PADNet model, we compared it against DeepPixBiS-based baselines on the OULU-NPU dataset under the four standard protocols. The evaluation metrics include APCER, BPCER, and ACER, which provide a comprehensive measure of detection accuracy. The results are summarized in Table 1 below.

Table 1. Metrics of our proposed model compared with other DeepPixBis-based models on OULU-NPU (Boulkenafet et al., 2017) for intra-dataset testing.

Protocol	Model	APCER (%)	BPCER (%)	ACER (%)
1	DeepPixBiS (George & Marcel, 2019)	**0.83**	**0.0**	**0.42**
	A-DeepPixBis (Hossain et al., 2020)	1.19	0.31	0.75
	Dual-PADNet (Ours)	2.55	**0.0**	1.27
2	DeepPixBiS (George & Marcel, 2019)	11.39	**0.56**	5.97
	A-DeepPixBis (Hossain et al., 2020)	4.35	1.29	2.82
	Dual-PADNet (Ours)	***0.52***	1.51	**1.01**
3	DeepPixBiS (George & Marcel, 2019)	11.67 ± 19.57	10.56 ±14.06	11.11 ± 9.4
	A-DeepPixBis (Hossain et al., 2020)	2.78 ± 3.47	11.16 ±16.45	6.97 ±7.57
	Dual-PADNet (Ours)	**2.60 ± 3.22**	**7.74 ± 12.33**	***5.17±5.72***
4	DeepPixBiS (George & Marcel, 2019)	36.67 ±29.67	13.33 ±16.75	25.0 ±12.67
	A-DeepPixBis (Hossain et al., 2020)	**3.86 ± 4.04**	**6.56 ±7.88**	**5.22 ±2.96**
	Dual-PADNet (Ours)	4.81 ± 7.42	17.55± 15.69	*11.18 ± 5.85*

As shown in Table 1, our Dual-PADNet architecture demonstrates superior performance among DeepPixBis-based models in Protocol II (ACER of 1.01%) and Protocol III (ACER of 5.17%). The outstanding result in Protocol II, which tests generalization to unseen spoofing devices, suggests that the contextual branch is highly effective at identifying artifacts from different printers and screens. While the model underperforms in Protocol I, it achieves perfect BPCER of 0.0%, indicating it never misclassifies a genuine user, a critical feature for usability. The performance dip in Protocol IV highlights the extreme challenge of generalizing across all variables simultaneously, a known issue for many PAD models.

5.5. Comparison with State-of-the-Art:

To evaluate the performance of the proposed Dual-PADNet, we conducted a comparative evaluation against several state-of-the-art presentation attack detection (PAD) models on the OULU-NPU dataset. The baselines include CDCN++, Bi-FAS-S, FAS-BAS, and DeepPixBiS, tested under the four standard protocols. Performance was assessed using the established error rates APCER, BPCER, and ACER, ensuring consistency with prior PAD studies. The results of this comparison are summarized in Table 2 below.

Table 2. Metrics of our proposed model compared with best models on OULU-NPU (Boulkenafet et al., 2017) for intra-dataset testing.

Protocol	Model	APCER (%)	BPCER (%)	ACER (%)
1	CDCN++ (Yu et al., 2020)	**0.4**	**0.0**	**0.2**
	Bi-FAS-S (Roy et al., 2021)	3.13	0.83	1.97
	FAS-BAS (Liu et al., 2018)	1.6	1.6	1.6
	DeepPixBiS (George & Marcel, 2019)	0.83	**0.0**	0.42
	A-DeepPixBis (Hossain et al., 2020)	1.19	0.31	0.75
	Dual-PADNet (Ours)	2.55	**0.0**	1.27
2	CDCN++ (Yu et al., 2020)	1.8	0.8	1.3
	Bi-FAS-S (Roy et al., 2021)	1.67	1.11	1.39
	FAS-BAS (Liu et al., 2018)	2.7	2.7	2.7
	DeepPixBiS (George & Marcel, 2019)	11.39	**0.56**	5.97
	A-DeepPixBis (Hossain et al., 2020)	4.35	1.29	2.82
	Dual-PADNet (Ours)	***0.52***	1.51	**1.01**
3	CDCN++ (Yu et al., 2020)	1.7 ± 1.5	2.0 ± 1.2	1.8 ± 0.7
	Bi-FAS-S (Roy et al., 2021)	**0.69 ± 0.68**	**0.28 ± 0.68**	**0.49 ± 0.63**
	FAS-BAS (Liu et al., 2018)	2.7 ± 1.3	3.1 ± 1.7	2.9 ± 1.5

	DeepPixBiS (George & Marcel, 2019)	11.67 ± 19.57	10.56 ±14.06	11.11 ± 9.4
	A-DeepPixBis (Hossain et al., 2020)	2.78 ± 3.47	11.16 ±16.45	6.97 ±7.57
	Dual-PADNet (Ours)	2.60 ± 3.22	7.74 ± 12.33	*5.17±5.72*
4	CDCN++ (Yu et al., 2020)	4.2 ± 3.4	5.8 ± 4.9	5.0 ± 2.9
	Bi-FAS-S (Roy et al., 2021)	**2.50 ± 3.16**	**3.33 ± 4.08**	**2.92 ± 3.41**
	FAS-BAS (Liu et al., 2018)	9.3 ± 5.6	10.4 ± 6.0	9.5 ± 6.0
	DeepPixBiS (George & Marcel, 2019)	36.67 ±29.67	13.33 ±16.75	25.0 ±12.
	A-DeepPixBis (Hossain et al., 2020)	3.86 ± 4.04	6.56 ±7.88	5.22 ±2.96
	Dual-PADNet (Ours)	4.81 ± 7.42	17.55± 15.69	*11.18 ± 5.85*

Table 2 compares Dual-PADNet with a wider range of state-of-the-art models. The key finding is that our model achieves the best overall performance in Protocol II with an ACER of 1.01%, outperforming even larger and more complex models like CDCN++ and Bi-FAS-S. This is a significant result, confirming the value of contextual information for generalizing across different attack instruments. Furthermore, our model achieves a state-of-the-art BPCER of 0.0% in Protocol I and a state-of-the-art APCER of 0.52% in Protocol II. While other models show stronger performance in Protocols III and IV, our model remains competitive in these protocols, especially considering it is by far the smallest and most efficient, as will be discussed in Section 6.

6. Discussion

6.1. Impact of Contextual Information:

By incorporating the full image context, our model captures additional cues that are often overlooked in face-only approaches. Background inconsistencies, edges of spoofing devices, and lighting discrepancies can provide valuable information for PAD.

6.2. Computational Efficiency:

Our dual-branch architecture, while more complex than single-branch models, remains efficient due to shared weights, a small backbone, and less frame usage during training. This makes the model suitable for deployment in real-time applications and on devices with limited computational resources such as edge devices. Table 3 illustrates different anti-spoofing models with their sizes.

To quantify the model's computational efficiency, performance was benchmarked on an NVIDIA RTX 3070 Ti GPU. Using a batch size of 1, the model achieved an average inference latency of 12.039 ms, enabling a throughput of 83.07 frames per second (FPS), while consuming a peak VRAM of only 6.46 MB.

Table 3. Model parameters comparison

Model	Parameters
CDCN (Yu et al., 2020)	2.25 M
CDCN++ (Yu et al., 2020)	> 2.25 M
Bi-FAS-S (Roy et al., 2021)	> 4 M
FAS-BAS (Liu et al., 2018)	> 10 M
DeepPixBiS (George & Marcel, 2019)	> 3 M
A-DeepPixBis (Hossain et al., 2020)	> 3 M
Dual-PADNet (Ours)	**1.4 M**

6.3. Limitations

It is important to acknowledge the scope and limitations defined by this dataset. The OULU-NPU database exclusively contains print and replay attacks and does not include other critical attack types prevalent in modern face anti-spoofing research, such as 3D Mask Attacks, Silicone Masks, cosmetic Makeup Attacks, or AI-generated Deepfake Attacks. Consequently, the model was trained and evaluated only on the specific artifacts associated with print and replay spoofs.

While our dual-branch approach is designed to capture a broader range of anomalies—and the context branch could theoretically detect cues like the visible edges of a 3D mask—its performance against these other attack types is unverified. We have not tested the model on other types of attacks, and its effectiveness against them cannot be guaranteed. This represents a clear limitation of the current study. Therefore, the results presented in this paper are specific to the print and replay attacks found in the OULU-NPU dataset. Future work should focus on evaluating and adapting the Dual-PADNet architecture on more diverse datasets that incorporate these modern attack vectors to fully validate its generalizability.

7. Conclusion and Future Work

We have introduced an efficient dual-branch convolutional neural network architecture for face presentation attack detection. Utilizing a dual-branch architecture that processes both facial and contextual information, our approach effectively addresses the limitations of existing methods. On the OULU-NPU (Boulkenafet et al., 2017) dataset, our model achieves state-of-the-art performance in protocols II and III among DeepPixBis-based models. Notably, it also outperforms all existing models to date in protocol II. Moreover, it delivers state-of-the-art results in the BPCER metric for protocol I and the APCER metric for protocol II. Remarkably, our model stands as the smallest among all anti-spoofing models, offering superior efficiency without compromising performance.

By offering an efficient and compact solution for face presentation attack detection, our model is particularly well-suited for deployment in industrial settings. This suitability is further reinforced by its state-of-the-art performance in Protocol II and competitive performance in Protocol I, which are the most relevant protocols for industrial access control systems, as they typically involve consistent camera types.

In future work, we plan to:

- Explore Different Weighting Factors: Investigate the impact of varying lambda in the loss function.
- Extend to Other Datasets: Evaluate the model's performance on other PAD datasets to assess generalizability.
- Use A-DeepPixBis (Hossain et al., 2020) Loss Function: The Angular binary cross-entropy Loss used in their paper achieved better results than vanilla binary cross-entropy loss. Using their loss function for the face pixel map might achieve better results.
- Add a Branch for Fourier Spectra: As seen by the Bi-FPN for Face Anti-Spoofing (Roy et al., 2021) paper, Fourier Spectra improves performance
- Better Augmentation: We believe that augmentations are the key to ensuring generalizability. In fact, our model outperformed on the second protocol where lighting and camera are fixed. This signals that more & different augmentations might help it outperform on protocols III and IV

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Gamification in Higher Education (Motivational Drivers from Omani Higher Education)

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Abstract

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Gamification has gained recognition as a pedagogical strategy that integrates game mechanics to strengthen motivation and engagement in higher education. This paper synthesizes motivation and language-acquisition theories: Self-Determination Theory, Communicative Language Teaching, and Krashen's Input Hypothesis; to explain how points, badges, leaderboards, levels, and challenges can be orchestrated to support the four ESL skills in foundation English courses. Focusing on Oman's vocational sector, we map mechanics to intended learning outcomes and to the needs for autonomy, competence, and relatedness, and we identify contextual moderators (infrastructure variation, assessment pressure, and cultural norms). Evidence from recent global studies indicates consistent gains in engagement, time-on-task, and perceived competence; pilot applications in Oman (e.g., Quizizz and Duolingo) show short-term motivational improvements, though longitudinal evaluation remains limited. We translate these insights into practitioner guidelines suited to variable connectivity: low-bandwidth tasks, hybrid online/offline challenges, formative feedback loops, and teacher communities of practice. The paper argues that context-adapted gamification, not generic points-and-badges, offers the best prospect for durable motivational gains and measurable language outcomes in Oman's vocational colleges.

Keywords: Gamification; Student Motivation; Higher Education; ESL; Oman; Self-Determination Theory; Communicative Language Teaching

1. Introduction

Vocational colleges have helped a lot in bringing education and practical skills needed by workers in Oman much closer together, especially during higher education over recent decades. Since there are students from many different educational and linguistic groups at these colleges, special attention is given to English classes. Being good at English gives students the chance to explore educational content, build ties across the globe and consider jobs in both their homeland and overseas. These courses work on improving a person's ability to listen, speak, read and write (Thomas & Baral, 2023).

Even though these schools matter a lot, they have difficulties teaching foundation English effectively. Among the main problems is that many students are not very motivated which leads to fewer people participating and learning the language. It has been found, through investigations, that numerous students become disinterested in their English classes by talking less, being careless with their lessons and neglecting to turn in their assignments. When students do not participate, they miss important aspects needed to improve their language abilities (Wang & Tahir, 2021).

The reason students often lack motivation in these classes is due to old teaching approaches. In most cases, students are taught to memorize facts from the teacher, who gives most of the lessons and doesn't link them to what students care about or go through day to day. As a result, students think English classes are not important and start to feel less interested (Wlodarski et al., 2025). For this reason, students have trouble meeting learning goals which delays their education and career success.

Because of these obstacles, educational researchers and teachers are finding means to help students remain motivated. Using points, badges, competitions and leaderboards in learning has led to positive results in motivating students. Learning a language becomes more satisfying and interesting when gamification is added which motivates users to continue practicing it often (Zeidan et al., 2023). By using games and activities in learning, autonomy, competence and relatedness theories make it possible to keep students engaged (Zichermann & Cunningham, 2021). For Oman's vocational colleges, using games brings a new chance to rejuvenate their foundation English instruction. While worldwide literature shows how helpful gamification is for language education, studies produced in Oman are still rare. The usefulness and feasibility of using games in education depends on classroom conditions, preparedness for new technologies, educational rules and what learners require (Seaborn & Fels, 2021).

It is important to see how gamification works in vocational education in Oman. These results will support teachers in developing sustainable approaches for teaching that are suitable for their region and motivated students. Zichermann and Cunningham write (2021), explaining, "you can't just think of gamification as points and badges; it's primarily about making the experience worthwhile to encourage people to engage." It reveals that gamification can encourage learners to get more engaged with language study. Also, according to Zeidan et al. (2023), putting lessons into a gaming framework tends to raise students' motivation and help them hold on to information better. This paper aims to learn if applying gamification tools can impact the motivation and English language skills of students in foundation English courses at vocational colleges in Oman, giving useful recommendations for similar institutions.

1.1. Objective of study:

In this study, the main objectives are: to consider important gamification approaches and their importance for language skills, to study important language acquisition theories that support gamification's value in education, to assess research conducted worldwide and nationally to judge its effectiveness and to offer helpful suggestions for introducing and improving gamified learning. In doing so, the paper helps to connect theory from innovative teaching with everyday classroom situations in Oman.

1.2. Structure of study:

After this introduction, Section 3 examines the research literature on game-based tools, theories of language learning and present-day empirical studies. Section 4 explains the way vocational education operates in Oman, showing which problems and opportunities foundation English face. Section 5 explains the methodological approach used in this research. Section 6 analyzes how gamification affects motivation and learning, covers regional examples and looks at the obstacles to implementing it. Section 7 includes useful guidelines for including gamification in lesson plans and learning how to teach with games. Finally, the paper ends by highlighting its main findings and offering suggestions on where to go next in research.

2. Literature Review

2.1. Gamification Tools and Mechanics

Gamification refers to the purposeful use of game design elements in non-game contexts to enhance learners' motivation, engagement, and persistence (Sailer et al., 2021).

In higher education and ESL settings, commonly used mechanics include points, badges, leaderboards, challenges/quests, levels, and rewards. Each serves a distinct pedagogical function when aligned with course intended learning outcomes (ILOs):

– Points provide immediate, low stakes evidence of progress for correct responses, on time submissions, and constructive participation—thereby operationalising formative feedback (Rodrigues et al., 2022).

– Badges function as mastery markers that make achievement visible, reinforcing academic self-efficacy and goal orientation (Nicholson, 2021).

– Leaderboards leverage social comparison and recognition to nudge participation; however, protective designs (tiered boards, personal best tracking) are recommended to avoid demotivating lower scoring students (Pelizzari & Gatti, 2023).

– Challenges/quests structure authentic, problem centred tasks with timely feedback that supports autonomy, persistence, and strategic effort (Marinensi et al., 2021).

– Levels scaffold complexity and sequence content into unlockable stages, clarifying pathways for skill development and maintaining optimal challenge.

– Rewards; symbolic or tangible, can sustain effort, but should complement (not displace) intrinsic interest (Koivisto & Hamari, 2021). In combination, these mechanics reframe routine activities as interactive learning experiences while keeping the instructional focus on ILOs rather than on "play" per se.

2.2. The Relationship Between Gamification Tools and Language Skills

Language learning requires competence across listening, speaking, reading, and writing. Gamification supports all four skills by maintaining practice intensity, enhancing feedback, and providing motivation:

– Listening: Gamified tasks with points and instant feedback sustain repeated exposure to audio input, strengthening comprehension (Jaramillo-Mediavilla et al., 2024).
– Speaking: Group challenges, role-plays, and leaderboards lower anxiety and increase frequency of oral practice, supported by peer collaboration (Ibisu, 2024; Hanus & Fox, 2021).
– Reading: Level-based reading activities scaffold comprehension gradually, while rewards and multimedia integration sustain engagement (Glover, 2021).

– Writing: Badges for milestones (drafting, revision, peer feedback) foster persistence and reflective learning, reinforced by gamified peer-assessment systems (Fernández-Antolín et al., 2021). By combining digital and offline gamified activities, teachers can support language development across contexts, even where access to technology varies.

Table 1: Gamification Tools Mapped to ESL Skills

Gamification Tool	ESL Skill Supported	Description
Points	Listening	Provides immediate feedback and encourages repeated practice with audio materials and micro-listening tasks.
Badges	Writing	Rewards process milestones (planning, drafting, revising) and creative outputs, reinforcing persistence.
Leaderboards	Speaking	Encourages participation and turn-taking in oral tasks via friendly competition (use tiered boards to protect low-anxiety learners).
Challenges	Reading	Motivates engagement with progressively difficult texts.
Rewards	All Skills	Offers tangible or intangible incentives to sustain motivation.
Note. Primary alignment is shown for clarity; each mechanic can support multiple skills depending on task design and assessment alignment.		

From the previous table, we can see the importance of gamification in English language teaching in improving learning skills. A number of peer-reviewed academic studies indicate that the use of gamification tools in university and vocational education settings significantly contributes to improving English language learning skills at various levels. A study conducted on university students showed that integrating Kahoot into vocabulary and reading activities led to a 23% increase in performance compared to the control group, with high levels of motivation and stimulation (Licorish et al., 2018).

In the area of listening, a pilot study on university students in vocational majors showed that the use of Quizizz led to a 15% improvement in average listening scores, reflecting the role of immediate competitive elements in enhancing focus (Wang & Lieberoth, 2016). Another study showed that gamification helped university students improve their academic writing using the

Classcraft platform, showing a significant 18% improvement in linguistic organization and accuracy compared to the traditional method (Sanchez-Mena & Martí-Parreño, 2017). More broadly, a meta-analysis of 11 university studies showed that gamification had a medium-sized effect (g = 0.517) on improving English proficiency, especially when elements such as points, rewards, and badges were incorporated into the learning activity design (Hung, 2017). These findings confirm that gamification is not just a recreational tool, but an effective pedagogical strategy for developing English language skills among university and vocational college students, provided it is integrated into a purposeful and targeted instructional design.

2.3. Language Acquisition Theories and Gamification

The effectiveness of gamification is illuminated through established language acquisition theories:

- Krashen's Input Hypothesis: Suggests language acquisition occurs when learners receive input just beyond their current level (i+1). Gamified levels and staged tasks operationalize this principle by gradually increasing difficulty (Castillo-Parra et al., 2022).
- Communicative Language Teaching (CLT): Emphasizes meaningful interaction. Gamified tasks (role-plays, team challenges, collaborative quests) create authentic communication opportunities (Richards & Rodgers, 2014; Montenegro-Rueda et al., 2023).
- Self-Determination Theory (SDT): Highlights autonomy, competence, and relatedness as psychological needs. Gamification satisfies these through choice in activities, clear progress indicators, and collaborative features (Chan & Lo, 2022; Liu & Lipowski, 2021). These frameworks show how gamification strengthens intrinsic motivation, supports engagement, and fosters sustained language practice (Raju et al., 2021).

2.4. Recent Global and Omani Research

Global studies consistently show gamification increases motivation, participation, and persistence in higher education (Torres-Toukoumidis et al., 2021; Mamekova et al., 2021). Key gains include stronger oral participation, better retention, and improved student satisfaction (López-Martínez et al., 2022). In the GCC region, research confirms gamification improves attendance and performance, while emphasizing the importance of culturally sensitive design (Alqahtani, 2022; Baah et al., 2023). In Oman, pilot applications of tools like Quizizz and Duolingo in vocational English courses have shown encouraging short-term results in motivation and self-directed learning (Torrado Cespón & Díaz Lage, 2022; Priyaadharshini & Maiti, 2023).

However, challenges such as inconsistent infrastructure and limited teacher preparation remain. This highlights the urgent need for more systematic, longitudinal studies that address Oman's unique cultural and institutional context.

3. Omani Educational Context

Oman is implementing major changes in education to ensure the workforce has the needed abilities for the future. The change is thanks in large part to vocational education giving students the skills needed for jobs in many technical and professional careers. With guidance from the Ministry of Education and the Ministry of Higher Education, Research and Innovation, vocational institutions provide certificate and diploma courses that pay a lot of attention to learning English. Such programs are designed to strengthen students' listening, speaking, reading and writing abilities to close language differences and support them in future advanced academic and workplace communication (Pelizzari, 2023).

Yet, these foundation English classes, in spite of being very important for the country's strategy, are often less effective in teaching people the language. Studies have shown that there are not enough motivated students in vocational classrooms. Many learners taking these courses have different English skills and resume-building is often hindered by their poor self-belief due to limited everyday use of English (Cespón & Lage, 2022). Because of this, students rarely engage in classroom discussions which keeps them from taking part fully in their studies. Likewise, traditional strategies of education using lectures and repetitive exercises do not keep the enthusiasm of different students over time. Many students tell us they find English lessons uninteresting which negatively affects their determination and taking part in class (Mohd et al., 2023).

The value placed on culture adds another challenge to student participation in Oman's vocational schools. Rules about how people should act in groups and the limits on gender interactions can shape classes and sometimes prevent mixed-gender learners from engaging actively. Also, some students consider English something needed just to succeed academically which lowers their desire to learn to communicate. A main focus on factual recall in schools takes away from learners practicing real-life communication and using new language in everyday life.

All of these challenges together demonstrate how vocational English programs in Oman must handle many different motivational, methodological and cultural issues. New methods that support motivation, address different learning needs, honor cultures and help students adjust to school and work are essential for successful language learning. Classroom examples reveal more about these difficulties.

In a foundation English lesson taught at an Omani vocational college, the teacher might direct students to read some texts and afterward work on questions that cover what they have read (Zainudin & Zulkiply, 2023). While a handful of students invest effort in the exercises, a good number are passive, depending on their peers for help. Educators find that most students hesitate to take part in speaking activities, as they are stressed by the possibility of saying something wrong in front of others. Because of these dynamics, it is important for teaching practices to support language skills and to make learners feel safe and motivated to practice (Ivarson et al., 2024).

Over the past few years, more and more Omani educators and policymakers realize the importance of new teaching strategies to deal with these challenges. Gamification may help students learn languages more passionately since it converts the process into something interactive with rewards. Even so, for gamification to work well in Oman's vocational colleges, they require preparedness and the necessary tools.

Today, there are big differences in how ready institutions are. In some colleges, the initial investment in digital resources has helped bring in online gamified learning platforms. Those who teach in these institutions are learning to use new technology, backed by professional programs aimed at increasing their digital literacy skills. As for other colleges, problems with unreliable internet, not having enough devices and a lack of training hold back the use of gamification on a broader scale (Huseinović, 2024).

Support from institutions covers more than technology and goes on to include adjusting the curriculum, encouraging administrators and ensuring teachers have regular training. If policies and incentives are not clear, the top-down structure in many vocational institutions could hold back the use of new innovative practices. Also, everyone involved in education should accept cultural change; successful gamification requires educators and learners to shift away from lectures and involve students more actively (Rincon-Flores & Santos-Guevara, 2021).

In spite of these difficulties, pilot efforts and some examples suggest that many are open to gamification. After using gamification, students say they enjoy learning more and are readier to join in, while teachers notice students work harder and use the language more often.

The existence of these early signals proves that wide-scale gamification needs sound frameworks that solve technological, teaching and cultural challenges all at once.

All in all, by insisting on strong foundation English skills, Oman's vocational education system is at a point where it can handle traditional motivation and engagement issues by using modern strategies such as gamification. It is important to become familiar with the local education system, notice the abilities of each school and help create an environment that supports change to uncover the best that gamified learning has to offer (Murillo-Zamorano et al., 2021).

4. Methodology (Conceptual/Theoretical)

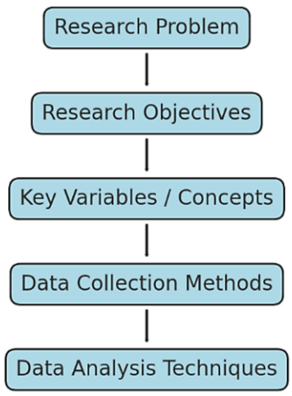

Figure 1. Methodological framework of the study illustrating the sequence from defining the research problem to the techniques of data analysis.

This study adopts a conceptual research design to investigate the role of gamification in enhancing student motivation and English language learning within foundation programs at Omani vocational colleges. Grounded in Krashen's Input Hypothesis, Communicative Language Teaching (CLT), and Self-Determination Theory (SDT), the study integrates perspectives from educational technology, language acquisition, and motivation theory to establish a robust theoretical framework.

Data were collected through a systematic literature review of sources published between 2018 and 2024 to capture recent developments in gamification and its educational applications. Searches were conducted in Google Scholar, Scopus, and ERIC, complemented by institutional and governmental reports. The selection was limited to peer-reviewed articles, conference papers, and academic books, with additional use of policy briefs and pilot program evaluations. Keywords included gamification, language learning, student motivation, vocational education, and Oman.

The study is temporally bounded within the 2018–2024 period and spatially focused on vocational colleges in Oman, while drawing on international research for comparative insights. While this conceptual approach enables the synthesis of cross-disciplinary perspectives, its reliance on secondary data limits the ability to capture local classroom realities. Nonetheless, the methodology provides a critical foundation for guiding future empirical studies involving classroom observations, surveys, and experimental designs.

5. Thematic Analysis & Discussion

5.1 Gamification's Impact on Motivation

Learners need plenty of motivation to keep working and overcoming objections. According to educational psychology, intrinsic motivation comes from feeling satisfied by the activity itself, while extrinsic motivation comes from those factors outside of the person. Many students do not feel motivated in vocational language classrooms because they find their tasks hard, think they are not useful or get bored with the way topics are taught. Not having the right encouragement slows down when children are learning languages and acquiring skills.

Gamification closes these gaps by using game methods that support both internal and external motivation. According to Ryan and Deci's theory published in 2017 called Self-Determination Theory, autonomy, competence and relatedness above all lead to motivation. Because of its design, gamification gives learners independence and freedom to select lessons, boosts their skills with feedback and updates and encourages team spirit through boards, group features and team exercises.

When students achieve a goal, gamified learning encourages the brain to release dopamine which makes learning much more engaging and pleasant (Hamari et al., 2014). As an example, after learners finish a task, offering them badges encourages them to keep learning. Csikszentmihalyi explained that with enjoyable gameplay, you stay more focused, helping you work more effectively. Many vocational language students become more certain of themselves and benefit when motivated by these techniques. Gamification helps to make learning more interesting, leading people to stick with education and gain skills.

5.2. Engagement and Performance Improvements

Making use of games in learning often excites students and improves outcomes. Engagement consists of presence, participation, interest, enjoyment, and attention. Gamification addresses these dimensions by encouraging continuous, purposeful participation in language activities. These claims are reinforced by recent empirical findings reporting increased preparation, attention, and vocabulary retention when gamified features are used (Priyaadharshini & Maiti, 2023).

In addition, frequent scores and progress updates help learners monitor performance and identify areas for improvement; feedback loops that are often missing from delayed, summative assessments. Social features such as leaderboards and team challenges promote collaboration and provide a low-stakes context for oral practice. Studies have also reported gains in creativity and critical thinking as students earn rewards for constructive group interaction (Sotirov et al., 2023).

5.3. Regional Case Studies

Recently, GCC countries have expressed an increased willingness to introduce gamification in education, since it helps solve student motivational and engagement problems. Focusing on gamified education in Asia is partly due to the worldwide movement to inject new technology into education to help people acquire languages for their professional and academic needs (Baah et al., 2023.

In 2020, Alqahtani did a pilot study with vocational English learners who used a curriculum with gaming elements. To increase student engagement, this curriculum consisted of badges, point systems and fun quizzes people could compete in. Because of the research, students had higher motivation, resulting in more Take part in classroom activities and improved their oral test grades. Many teachers found that using games details in their teaching made lessons fun and pleasant for their students which removed the worry that prevented many from engaging in class activities. In addition, it pointed out that using gamification made students more likely to practice and communicate in English with confidence.

Gamification was introduced by Baah et al. (2023) during language lessons in technical colleges in the UAE. Through mix-method research, they discovered that gamification was linked to higher student attendance and greater interest in doing language activities. The use of gamification led students to report more pleasure and readiness to work with language resources, mainly because they got instant feedback and prompt rewards. Still, some obstacles were found in the study, including different levels of technology use among institutions and not enough training for teachers in the use of gamified methods which held back the program's results.

Even without extensive research on gamification in Oman, the government reports and test cases so far suggest promising results. The Oman Ministry of Education (2022) implemented Quizizz and Duolingo on digital platforms in a number of vocational colleges to help motivate the students. At the beginning, these programs showed that students were more eager to try language exercises by themselves (Priyaadharshini & Maiti, 2023). Despite these signs, studies that measure long-term progress have not been done extensively. Problems with internet access and a lack of devices, along with not enough teacher preparation, make it hard to roll out gamification everywhere in the nation.

All of these examples prove that gamification can transform learning languages and also suggest that more local adjustments are crucial. Succeeding in this kind of learning requires focusing on cultural norms, improving teacher skills and investing in technology to design gamified learning environments that fit the GCC region's various educational needs (Ng et al., 2023).

5.4. Classroom Implementation Barriers

Even though gamification helps students become more interested and active in their learning, putting it into practice within Omani vocational classrooms is not easy because of several important challenges. There are many obstacles, including not enough people, lack of modern resources and challenges tied to culture which all need to be handled to realize gamification's potential.

A main hurdle is that too many teachers do not have the necessary preparation. Most teachers at Oman's vocational colleges are not very familiar with using technology in teaching and have little knowledge of games in education. If they don't receive training, teachers can have difficulty making games work well in their teaching and fully use the benefits these tools offer. As a result, implementers often don't utilize gamification enough or apply it improperly, so the enthusiasm it could create fades (Aguiar-Castillo et al., 2022). For this reason, organizations must invest in full professional development programs. In such programs, teachers should learn both how to use different gamified platforms and how to add gamification to their lessons that matches the goals of language learning.

Access to resources is also a serious obstacle. While certain Omani vocational colleges have the necessary technology resources, others are working with very basic infrastructure. Constantly changing internet connections and a shortage of devices prevent students from logging on to online learning often. In answer, certain institutions use rules and tasks that can be done offline with games designed on paper or by gathering in person for challenges. Still, this approach typically does not provide the instant interaction and instant feedback that technology can which makes engagement in gamified activities less desirable (Alasmari, 2020).

Apart from technical obstacles, what people believe and how they act often affects whether gamification is accepted. Traditional teaching, where educators lecture to students, can be something both teachers and students resist changing. Its lighthearted or relaxed approach sometimes makes it hard to convince schools with strict traditions to use gamification. Furthermore, differences in gender in classes with both sexes in Oman may prevent students from working together in games, so ways have to be found that respect local customs and are open to everyone.

Also, issues with curriculum and administration keep gamification from being embraced. Because of these critical language proficiency exams, teachers often concentrate on studying for them instead of exploring other teaching techniques. In the absence of concerted institutional support for using gamification, teachers could find it hard or unappealing, to develop and monitor learning with games (Hazdun, 2025).

Tackling these various problems means combining teacher improvement through training over time, improving IT systems, helping educators and students recognize gamification's educational benefits and establishing favorable policies in favor of inventive teaching.

The following conceptual graph illustrates comparative motivation levels measured through pre- and post-gamification surveys and observations in foundation English classes.

Table 2: Motivation Levels Before and After Gamification

Motivation Aspect	Before Gamification	After Gamification
Intrinsic Motivation	Low	High
Engagement Level	Moderate	High
Participation Frequency	Low	Moderate to High
Confidence in Skills	Low	Moderate to High

The results presented in Table 2 clearly demonstrate the positive impact of gamification on students' motivational dimensions in foundation English classes. Prior to implementing gamified activities, learners exhibited low levels of intrinsic motivation, participation frequency, and confidence in skills, with only a moderate level of engagement. Following the integration of gamification tools, however, there was a marked improvement: intrinsic motivation shifted from low to high, engagement rose from moderate to high, and both participation and confidence increased to moderate-to-high levels. These outcomes suggest that gamification not only fosters enjoyment but also creates a learning environment in which students feel more encouraged to participate and develop their language abilities.

These improvements are consistent with previous experimental studies. Likorish et al. (2018) reported that integrating Kahoot! increased student engagement rates and improved classroom dynamics, with learners expressing significantly higher levels of motivation compared to pre-intervention measures. Similarly, Wang and Lieberoth (2016) found that gamified quizzes enhanced focus, engagement, and enjoyment, leading to a stronger desire to engage in language tasks. In another study.

6. Conclusion

In this study, rigorous analysis is given to how introducing gamification improves student motivation and supports the acquisition of English in foundation courses at vocational colleges in Oman. The research combines well-established motivation theories with well-known language learning approaches and the results show that including points, trophies, leaderboards and challenges in games supports learners in an enjoyable environment. As a result, individuals manage their own learning, continue gaining knowledge, practice interacting with others, develop attention to the course and improve language competence. Omani case studies support the view that gamification is a new teaching strategy that matches with the local culture and school environment. In spite of issues like not enough teacher preparation, low availability of educational materials and a fixed curriculum, gamification makes basic English learning fun and meaningful. The study illustrates that continuous improvement for teachers and a solid educational system help improve the results of gamified learning. In general, it supports the discussion of new educational ideas in Oman by urging the use of context-appropriate gamification. After learning from the research, educational stakeholders are encouraged to embrace gamification to help solve motivation problems and aid with learning different languages. Empirical studies should be carried out to confirm these understandings by seeing them applied in classrooms, getting student opinions and measuring the results of what is learned. Such findings will guide people in teaching methods and progress in Oman's education system.

7. Summary of Research Findings

- Gamification tools (e.g., Kahoot, Quizizz, Classcraft, Duolingo) incorporate mechanics such as points, badges, leaderboards, and quests, which positively influence learner motivation and create more interactive classroom environments.
- The integration of gamification into English language learning demonstrates a clear positive relationship with improved language skills, particularly in vocabulary acquisition, reading comprehension, and speaking fluency.
- Language acquisition theories (Krashen's Input Hypothesis, Communicative Language Teaching, and Self-Determination Theory) provide a strong theoretical foundation, explaining how gamification fosters input, interaction, and intrinsic motivation in language learning.
- Global research highlights consistent benefits of gamification for motivation, engagement, and achievement, while Omani studies reveal growing interest but still limited empirical evidence in vocational education contexts.
- Within the Omani higher education setting, gamification aligns well with the national push toward digitalization and innovative pedagogies, but practical application remains uneven across institutions.
- The conceptual methodology demonstrates that gamification has a strong impact on student motivation by enhancing enjoyment, competitiveness, and sense of achievement.
- Evidence also indicates improvements in engagement and academic performance, with gamified tasks increasing participation rates, task completion, and performance scores compared to traditional methods.
- However, classroom implementation barriers were identified, including limited digital infrastructure, inconsistent teacher training, and concerns about balancing fun with curriculum goals.

8. Practical Recommendations

Based on the findings of this study and insights derived from the reviewed literature, several practical recommendations are proposed to guide the effective integration of gamification into English language learning at the tertiary and vocational education level. To ensure clarity and applicability, the recommendations are organized into four categories: classroom strategies, gamified tools, teacher training, and institutional readiness and policy. This structured approach highlights the multi-level responsibilities of teachers, learners, and institutions in fostering sustainable and motivating gamified learning environments.

8.1. Classroom Strategies

- Implement point systems, digital certificates, and badges to encourage participation and reward achievement.
- Use leaderboards to promote positive competition while providing support to lower-achieving students.
- Design thematic quests and challenges that integrate listening, reading, writing, and speaking tasks.
- Apply short, time-limited activities and progressive levels to sustain student motivation and focus.
- Align gamified activities with curriculum objectives and ensure regular evaluation.
- Encourage collaborative work through group-based gamified tasks that foster teamwork and communication.
- Differentiate gamified activities according to students' proficiency levels and individual learning needs.

8.2. Gamified Tools

- Utilize Kahoot and Quizizz for interactive quizzes and real-time feedback.
- Incorporate Duolingo for vocabulary and grammar practice through short, engaging lessons.
- Adopt Classcraft to enhance collaborative learning through team-based adventures and quests.
- Use digital badges to motivate continuous achievement and recognize milestones.
- Employ offline alternatives such as flashcard tournaments and language board games in low-resource settings.

8.3. Teacher Training

- Provide training on designing, implementing, and evaluating gamified activities.
- Organize workshops, peer mentoring, and continuous professional development programs.
- Strengthen teachers' confidence in integrating technology into pedagogy while aligning with curricular goals.

8.4. Institutional Readiness and Policy

- Invest in infrastructure, including internet access, digital devices, and learning platforms.
- Establish clear institutional policies that standardize and sustain gamification practices.
- Support curriculum innovation by encouraging flexible and creative teaching approaches.
- Create professional learning communities for teachers to exchange gamification practices.
- Conduct periodic evaluations of gamification's impact on motivation and learning outcomes.
- Connect gamified activities with real-world and workplace-relevant scenarios to increase practical value.

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