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Research Article

The Value of Transnational Collaborative Capstone Projects for Final-Year Information Technology Students: Three Case Studies

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ABSTRACT

The global Covid-19 pandemic demanded many changes to the practices of professional fitness trainers who had previously been able to work face-to-face with their clients in fitness centers. To address their needs, the German business Strength Coaching Online began researching and developing their own custom web and mobile application in partnership with the Auckland International Campus of Otago Polytechnic. This article presents our background research and three case studies from the student projects undertaken in collaboration with Strength Coaching Online. Final-year Software Engineering students, their lecturers, with an experienced fitness coach, and an academic researcher have participated in each project. Together, they collaborated on the design and development of important aspects of the applications. During the third project, our ongoing AIRES Artificial Intelligence initiative emerged from the research of one of the student co-authors, driven by a dataset captured by the coach and their clients over many years. This third case study is presented in detail to show how in an Experiential Learning environment, students can develop complex systems such as AIRES. In this first phase of the research, AIRES explored the ethical use and management of medical-grade fitness data, the retrainability of Small Language AI models, and cost-effective computer hardware implementations that will be environmentally sustainable.

Keywords: Capstone IT Projects, International Collaborations, Experiential Learning, Strength Training, Artificial Intelligence, Small Language Models.

INTRODUCTION

During the Covid-19 pandemic, the global health and fitness industry underwent significant transformations. Due to health restrictions and lockdowns, fitness coaches could no longer work with their clients face-to-face in fitness centers (Füzéki et al., 2022; Jankowska, 2021). Coaches are professionals who provide support and guidance in ways similar to other health practitioners, hence, personal contact is a vital aspect of a coach's work. Working alongside their clients, observing and guiding, they help them to follow an individualised training plan tailored to their personal needs (Craig & Eickhoff-Shemek, 2009).

To alleviate the lack of contact caused by the pandemic, coaches began to enhance their use of public social media platforms and video conferencing (Füzéki et al., 2021). Lindholm (2023) discusses the advantages of application-based training, including flexibility and the reinforcement created by accurately tracking performance. Studies show that a hybrid model that augments in-person coaching sessions with a specialised, all-in-one application enhances the training experience of the client.

This article profiles the transnational initiatives of the fitness organisation Strength Coaching Online (SCO), based in Tübingen, Germany and the students and staff of the Auckland International Campus (AIC), based in New Zealand. Transnational collaborations are arrangements or processes in which participants work together spanning the boundaries of two or more countries (Rouse, 2019). SCO has always maintained an active research focus. During the Covid-19 pandemic they created their own remote coaching resources using online spreadsheets and high-quality training videos. After the pandemic, SCO began the design of their own web and mobile remote training application by establishing a long-term research and development initiative with the students, lecturers, and researchers at AIC. Final-year undergraduate and postgraduate computer science students participated remotely with SCO, delivering prototypes of different, specialised, aspects of the new solutions. The scope of the research and development included User Interface (UI) and User Experience (UE) design, cyber-security, software development, and investigating Artificial Intelligence (AI) initiatives using Small Language Models. Students were guided by the SCO coach in regular remote online meetings. The students were provided with training resources and example fitness data from SCO clients they could use under an Ethics Agreement that included a Non-Disclosure Agreement. They also worked on-campus with their course lecturers and a full-time academic researcher.

The contributions of this article include an evaluation of aspects of the collaborative design, management, prototyping, and development that was undertaken. A brief discussion of the contributions of the first two projects is followed by a deeper exploration of the most recent of the individual 18-week projects. This project led to the AIRES AI that will be one of the primary focuses of the future research.

LITERATURE REVIEW

Final-year Capstone Information Technology projects allow students to apply many of the skills they have learnt on previous courses in a single, focused project with clear requirements, goals, and objectives. When a project includes an external, often transnational company as both a sponsor and technical advisor, the experiences of the students are more grounded in real-world industry needs and situations. AIC Studio projects can be either individual or team-based.

Experiential Project Based Learning within Transnational Projects

AIC teaches Software Engineering in both dedicated topic courses and via six separate Studio courses, spread over the full three years of their Bachelor of Information Technology (BIT) degree. Hewage and Imbulpitiya (2025) explain the role that guided student reflection and peer-review plays throughout the Studio courses. This aligns with AIC's emphasis on Experiential, Project-Based Learning (PBL), where all theory taught in courses is reinforced with practical design and development projects. Students are more willing to seek post-project references from their clients and include these in their Curriculum Vitae, which helps them when they apply for positions after graduating.

PBL typically de-emphasies or replaces traditional teacher-centric learning approaches, encouraging real-time mentoring rather than instruction. Boss and Krauss (2018) explain how PBL offers opportunities for deeper learning for students who are willing to engage more thoroughly in real-world application and system development needs and experiences rather than in simulated or artificial teacher-created projects. This drives more realistic critical thinking and often deeper engagement in the development and research, since the outcomes of their work can initiate valuable outcomes and deliverables for their clients.

Structured Reflection and Peer Feedback

Imbulpitiya and Hewage (2025) discuss the role structured reflection and peer feedback play to support PBL. They emphasise the role of abstract data modeling and formal database entity relationship diagram design in software projects. They explore the role of Scenario Analysis coupled with Peer Review to create sound designs. By the time students commence their final Capstone projects, these design practices should have been established as sound, natural ways of thinking and approaching new problems in unfamiliar domains. They will have engaged in increasingly more complex problem tasks as they progress through the prior four Studio courses during their three-year degree.

CASE STUDIES OF THE THREE PROJECTS

Over a one and a half year period, AIC students and academic staff participated in three different projects with SCO.

Project One - User Interface and User Experience design

The first project in 2024 focused on UI and UX design for the new SCO web and mobile applications. Working closely with the coach, the graduate student identified key aspects of the current SCO website that should be preserved and migrated into the new applications. The Studio project was complemented by a parallel AIC User Experience Design course that the student was enrolled in during the first phase of their Studio project.

Through interactive collaborations with the coach, high-quality design images and example code prototypes were created that implemented the new dark-theme UI that SCO desired. Figure 1 illustrates the evolution of the original SCO website into the new dark theme while preserving and extending the original scope. The portfolio of resources delivered by the end of this first project was extensive and still guides the current UI/UX implementation during later stages of its ongoing development.

Figure 1: The evolution of UI for the Strength Coaching Online web application.

Project Two - Cyber-Security education and resilience

The second project performed penetration testing and security hardening for the SCO software hosting platform. This was an iterative evaluation that mitigated each security vulnerability that was found using tools that the graduate student was learning. The Studio project was complemented by a parallel AIC cyber-security course led by one of the authors that the student was enrolled in at the same time as their Studio project.

A comprehensive small-team security practice guideline was created by the student during the project and trialed with SCO. The cyber-security penetration testing evidence and recommendations led to the replacement of the SCO firewall with a more secure device to mitigate vulnerabilities that were exposed by the penetration testing. The research was also published as an academic journal article (Nguyen et al., 2025).

Project Three - AIRES - an AI assistant for assisting coaches to evaluate their clients progress

Building on these foundations, the third Studio project led to the development of our ongoing AIRES AI initiative which is creating a Small Language Model (SLM) interactive AI assistant to work alongside coaches. Clients report their progress from each training session in the new SCO web and mobile application. AIRES can mine this data and will incorporate innovative approaches to Model retrainability, secure and ethical management of medical-grade client data, and platform sustainability.

AIRES seeks to embody three core aspects in its name which are important to both SCO and the researchers. The “R” addresses the need for the AI to be retrainable after initial training by the coach and researchers. This is an important requirement (Katsikarelis, 2025). AIRES is designed to work alongside the coach while they are evaluating the progress a client has reported. The amount of feedback coaches need to provide often results in a high workload, so using an AI as an assistant would offer significant advantages. Long-term trends in a client’s training regime are valuable indicators that help coaches adjust a client’s training schedule to refine their progress. However, when an AI does not analyse a client’s results correctly, it should be possible for the coach to correct the AI’s interpretation of that data. This retraining would be the normal response of a senior coach who is training a human apprentice coach.

The AI models were trained on a rich dataset that SCO has captured in well structured spreadsheets. The core data for each exercise a client performs in a gym session includes the type of exercise and the number of times it is repeated, as well as the recommended weights and Rate of Perceived Exertion (RPE) (Refalo et al., 2025) for resistance exercises.

Clients agreed to share their data for use in this research under an OPAIC Ethics Agreement. The data was found to exhibit a high degree of consistency, which makes it an ideal candidate to mine with an appropriate AI model. The AIRES research facilitated a series of different AI prototypes and approaches that were trained and refined on this data.

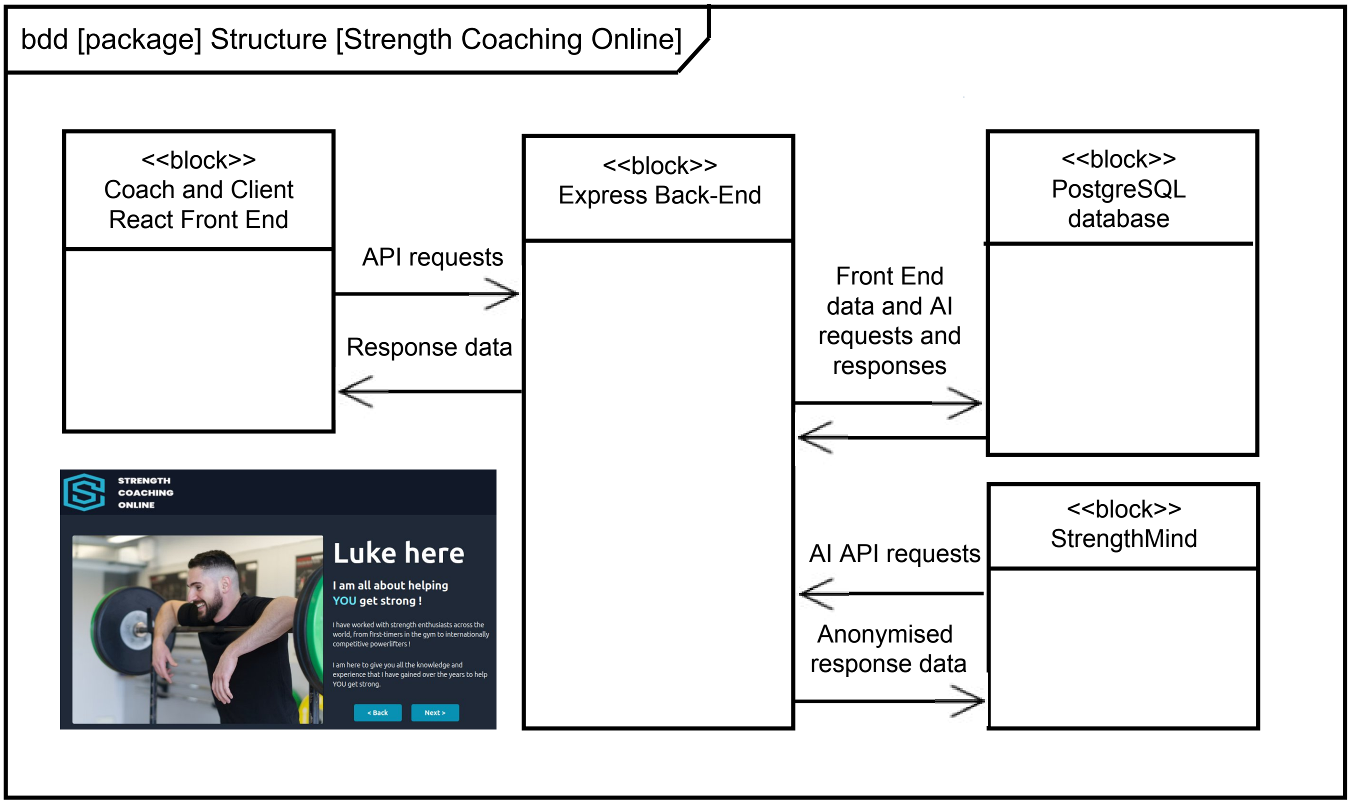
The second aspect “E” emphasises the ethical considerations that apply when handling medical grade data. At the present time, the authors do not believe that AIs should interact directly with clients. Fig 2 shows the Application Programming Interfaces (APIs) that the Back-End provides to allow the clients and coaches to access SCO data. The AI only has access to a restricted set of APIs to ensure that all client data is anonymised correctly. While coaches can identify each client by name, the AI can only access fields such as age, gender, weight, and the training data, identified by a unique numeric key per client. This preserves the client’s privacy. All data exchange is mediated by secure authentication tokens (Solapurkar, 2016) where the AI operates as an authorised user on the system with restricted privileges.

The third aspect “S” is Sustainability. AIs are energy-hungry and expensive to train and run. The AIRES research seeks to produce high-performing, well-trained Small Language Model AIs that are energy efficient. The following sections illustrate the scope and depth of what a student can experience and achieve in a well-managed Studio environment.

StrengthMind - the first AIRES prototype

StrengthMind is the first operational AI prototype developed within the AIRES research programme. It explores how interpretable, lightweight AI can support strength coaches as their clients follow a programme of exercises arranged into focused periods of time with a specific goal called Blocks (V. Issurin, 2008; Wackerhage & Schoenfeld, 2021). Coaches make incremental, Block-level training programme adjustments to refine each client's performance.

Figure 2: The architecture of the SCO Front End, databases, and StrengthMind mediated by the Back-End



Within the system architecture shown in Figure 2, StrengthMind operates as the analytic core of AIRES. It receives anonymised numeric training data through restricted APIs, processing the information using a Tabular Deep-Learning model. This is an approach designed specifically for structured, heterogeneous numeric datasets where sequential feature selection improves both accuracy and interpretability (Arik & Pfister, 2021). This produces outputs intended to better inform a coach's decisions, allowing StrengthMind to support AIRES's three pillars:

- **Retrainability**: the model and the Extract, Transform, Load (ETL) pipeline can be re-trained rapidly as new blocks accumulate or as coaches refine decision labels. In later versions of the model, the coach will be able to provide feedback to AIRES, augmenting the real-time unsupervised retraining as StrengthMind continues to mine new data added by clients each day.
- **Ethical data management:** only anonymised client data, provided with their consent, is ingested by the AI pipeline. This is consistent with contemporary guidance on privacy-preservation and ethical AI use in sport and health contexts (Dwork & Roth, 2014; Kim et al., 2025). The AI also has no direct access to external networks and hence is unable to compromise the system's integrity model by sharing data on the open internet.

- **Sustainability:** the model runs efficiently on commodity hardware rather than cloud-scale generative systems, reducing both compute and energy costs (Hollmann et al., 2022).

The prototype provides an early demonstration of how interpretable, energy-efficient AI can work alongside coaches rather than replace them, forming the foundation of the larger, long-term AIRES initiative.

Interpreting Coaching Data

SCO provided historical training data in spreadsheets organised into intervals called Mesocycles, also referred to as Blocks. Blocks are periods of training that focus on achieving particular goals or improving certain attributes, such as building strength, muscle size, or endurance. Each block contains:

- **Session-level data:** planned versus actual sets, repetitions, the load in kilograms the client was lifting in certain exercises, and the clients own estimated RPE for each scheduled exercise.
- **Coach notes:** qualitative comments regarding technical performance, contextual stressors, and adaptation. These include instructions and recommendations from the coach prior to the training session as well as feedback comments from both the client and the coach after the session.

Coaches interpret this combination of objective and subjective information using established strength and conditioning principles (Haff & Triplett, 2015; V. B. Issurin, 2016). Decisions to increase, maintain, or reduce the clients training load depend on several factors. Performance trends include changes in the client's own Estimated One-Repeat Maximum (e1RM) (Helms et al., 2016). The discrepancies between planned and performed volume can be interpreted as wellness indicators, which often precede changes in a client's performance capacity (Gabbett, 2020; Saw et al., 2016).

ETL and Feature Engineering

Before the automated feed of data from the back-end systems was developed, a reproducible ETL pipeline was created to convert heterogeneous spreadsheets into consistent weekly and block-level datasets. The pipeline parses raw spreadsheet data into structured session tables. The aggregated weekly summaries include features such as the e1RM mean over all the lifts, the delta in each lift, set-completion rates, and the consistency of the repetitions performed for each exercise. The pipeline also removed all identifiable client information before analysis. The resulting dataset provides a structured representation of the objective and subjective cues underpinning coaching decisions.

Methodological Pivot: From Language Models to Tabular Deep Learning

Initial investigations explored Small Language Models (SLMs), lightweight transformer-based generative models designed for efficient text processing and domain-specific natural language tasks (Lu et al., 2024). This included interpreting training notes and producing natural language suggestions. However, three limitations made this approach unsuitable for early-stage development:

1. **Weakness in numeric reasoning:** SLMs generated fluent output but struggled to interpret numerical data such as e1RM trends, adherence rates, and workload discrepancies. This aligns with recent reviews highlighting hallucination and instability when LLMs are applied to quantitative health-adjacent domains (Ji et al., 2023; Thirunavukarasu et al., 2023).

2. **Lack of domain grounding:** SLMs produced generic coaching statements that were not tied to specific weekly metrics, limiting their usefulness for block-level decision support.

3. **Data scale mismatches:** Fine-tuning an SLM requires hundreds or thousands of well-structured prompt–completion pairs (Dettmers et al., 2023), far exceeding the initial dataset size.

The Pivot to TabNet

Given the dominance of structured numerical features in SCO's dataset, the project shifted to use TabNet, an attentive neural architecture designed for tabular data (Arik & Pfister, 2021). TabNet supports sequential feature-selection through *attentive masks*.. These provide built-in interpretability for both global and local decision behavior and end-to-end learning with minimal hand-crafted feature selection. It also allowed for efficient training on modest hardware. This made TabNet a strong fit for the early StrengthMind prototypes.

Refining the Dataset, Proxy Labels, and Training Design

An initial feasibility dataset of ten anonymised training blocks consisting of 63 weekly samples from a competitive strength athlete was used. The data exhibited excellent internal consistency but limited sample size and class imbalance. True coach-annotated block decisions were incomplete, so proxy labels were created with input from the coach based on documented coaching criteria (Haff & Triplett, 2015; Helms et al., 2016; Zourdos et al., 2016). This helped to identify positive e1RM trends, good adherence, and manageable fatigue. Small positive trends were identified where the client execution was stable. There were indications of where the coach should "Deload" the plan. Deloads do not necessarily address under-adherence. Rather, they address fatigue or psychological staleness which could lead to adherence issues that are not directly related (Imbach et al., 2022; Vermeire et al., 2021).

The AI model training process included the use of PyTorch (Paszke et al., 2019) as a model for implementation of the TabNetClassifier (Arik & Pfister, 2021). The Loss function incorporates cross-entropy with class weights to handle imbalance. The Validation was a stratified five-fold cross-validation (Kohavi, 1995). Optimisation relied on the Adam-based optimiser (Kinga, Adam, et al., 2015), which was the default in the implementation used. The model also addressed Regularisation (Prechelt, 2002) to mitigate early stopping on validation loss. This was run on a local NVIDIA RTX 3070 GPU. This design emphasised stability and sustainability while accommodating the constraints of small-sample modeling.

Findings: Predictive Performance and Interpretability

Predictive Performance is the ability of an AI model to accurately predict future outcomes based on both its current and previous historical data. It is an indicator of how well the model's predictions align with actual results when considering biases and overfitting (Hastie et al., 2010). With the first small and unbalanced dataset, the model achieved a validation accuracy of approximately 46%, with stronger performance on the majority of cases where the Increase class indicated that the clients performance was improving. However, there was weaker detection of both the Maintain and Deload classes due to label imbalance. Such patterns are typical in small-N, imbalanced sports-science datasets (Halperin et al., 2018; Krawczyk, 2016).

TabNet's primary strength was its interpretability. Both global and local explanations aligned closely with strength-coaching logic, verified by discussions with the SCO coach. The most influential features included:

- Identifying performance based on the e1RM mean for major lifts, calculated from the e1RM of the first week of a block and the last week across a block of training.
- Recognizing trends in the clients actual set totals for squat and accessory movements.
- Highlighting discrepancies between their planned and actual workload in each session, measured sequentially during the current block.

Figure 3 shows the Confusion Matrix for the TabNet classifier on the validation set. The results indicate reliable detection of the dominant Increase class, while Maintain and Deload were under-detected, reflecting the effects of class imbalance and limited sample size.

Figure 3: The TabNet Confusion Matrix

```
Confusion matrix:
 [[0 1 0]
 [3 6 1]
 [2 0 0]]
Accuracy: 0.46153846153846156
```

Studies show that these metrics are central to block-level evaluation in strength training (Helms et al., 2016; V. B. Issurin, 2016). Local Explanations included data identified in the Local attentive masks, which highlighted decisions on the part of both the coach and the client driven by rising e1RM and high adherence. There was evidence of Deload decisions being made which had been driven by adherence shortfalls and negative workload trends. Over the block, coach decisions were evidenced by stable performance with small improvements. These Local explanations helped illustrate why each decision was made, reinforcing the model's suitability for a Coach-in-the-Loop workflow (Ribeiro et al., 2016; Rudin, 2019).

Summary of Insights

Tabular modeling is well-suited to mining strength-training data. The structured numerical data favors attentive tabular architectures over language models (Arik & Pfister, 2021; Shwartz-Ziv & Armon, 2022). Feature masks and per-sample attributions must provide reasoning aligned with coaches' mental models, an essential requirement for adoption in practice (Rudin, 2019).

However, data constraints obviously limit predictive performance. Small sample sizes, class imbalance, incomplete wellness fields, and proxy-label noise constrained accuracy—challenges that are familiar across applied sports analytics (Claudino et al., 2019; Halperin et al., 2018). Sample sizes will almost always be small and SCO explained that even if a coach has been working with a client for many years, the early data is no longer relevant as clients will have changed significantly over time as they continued to train.

Ethics, Retrainability, and Sustainability remain a key drivers for this ongoing research. All initial training data was collected under informed consent and de-identified manually by the coach before processing. As StrengthMind is developed further, the AI modules will still only have access to anonymised data. This is being facilitated by providing the AI with access to a restricted set of APIs as shown in Fig 2. These supply numeric training data as well as age, gender, and body-weight. Personal identification data such as names or other references cannot be accessed by the AI to ensure that the integrity of the data is not compromised. While the coach will see responses on their screen related to named clients such as "Emily " or "George" the AI will only know them by their unique client ID number. This number is the primary identifier in each training data record that the AI has mined from the SCO database so it can report findings consistently without needing to identify clients by name. The goal is to always have recommendations framed as decisions made by the coach rather than automated prescriptions from the AI to the client (Kim et al., 2025).

Some degree of Retrainability of the data model was exhibited in the ETL and modeling pipeline but the design will need significant refinement to achieve the ease of use and levels of retraining desired. The approach mirrors coaching practice: iterative refinement based on new evidence. Interpretable Tabular Models reduce the need for repeated, energy-intensive retraining (Hollmann et al., 2022).

Sustainability remains paramount, considering the reports of the amount of electrical power current AIs demand (Strubell et al., 2019). Obviously, our energy demand will grow for the additional GPUs required as the number of clients increases. However, new lower-cost resources from manufacturers such as Intel (Han et al., 2015) will help to address this aspect of the AIRES architecture.

The next iteration of StrengthMind will support the broader AIRES vision through data expansion that will increase the dataset to 50–100+ blocks across multiple athletes. We aim to improve the class balance through targeted data collection and improved Label Fidelity. Proxy labels will be replaced by adding coach-annotated decisions to reduce uncertainty (Frénay & Verleysen, 2014). There is also an opportunity to enhance Subjective-Wellness Capture, ensuring consistent collection of subjective indicators, which often outperform objective proxies (Gabbett, 2020; Saw et al., 2016).

Benchmarking against alternative models will allow us to compare TabNet with LightGBM (Ke et al., 2017), XGBoost (Chen & Guestrin, 2016), CatBoost (Prokhorenkova et al., 2018), NODE (Popov et al., 2019), and TabTransformer (Huang et al., 2020). This will evaluate accuracy and interpretability trade-offs (Chen & Guestrin, 2016; Huang et al., 2020; Ke et al., 2017; Popov et al., 2019; Prokhorenkova et al., 2018). There are also opportunities to implement a Hybrid Language Interface. Adding a lightweight SLM layer to handle natural language queries will ensure that we leave numerical reasoning to the tabular models (Dettmers et al., 2023; Lu et al., 2024). Hence, the implementation of an interactive Coach Dashboard will provide a visual interface summarising weekly trends, predictions, and feature attributions to enhance coach–AI collaboration (Decroos et al., 2019).

Conclusions and Future Research

This article has illustrated the value to students of participating in long-duration, transnational collaborations with highly experienced industry professionals. Not only do they gain practical development and interpersonal skills, the students also actively contribute publications and research outputs that enhance the body of knowledge. These are frequently used by subsequent students to facilitate new phases of on-going projects.

AIC's experience over many iterations of Studio projects has demonstrated that final-year students benefit the most by working on projects that are aligned with and driven by the real needs of commercial clients. Clients such as SCO, who value the growth that on-going research provides to their organisations, facilitate experiences which are genuinely appreciated by students.

The previous section outlined the next stage of the AIRES research that will be conducted using later iterations of StrengthMind. Allied with that, the mobile version of the application will be developed further, augmenting it with real-time video collaboration capabilities to explore how SCO can facilitate secure, real-time remote personal coaching sessions in a gym.

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