Multi-dimensional Trajectories of Expertise in Engineering: Perspective from Epistemic Frame Theory

Amit Paikrao
Centre for Educational Technology
Indian Institute of Technology Bombay
Mumbai, India
amitpaikrao@iitb.ac.in

Vishwas Badhe
Centre for Educational Technology
Indian Institute of Technology Bombay
Mumbai, India

Indrayani Nishane
Centre for Educational Technology
Indian Institute of Technology Bombay
Mumbai, India

Jyoti Shaha
Centre for Educational Technology
Indian Institute of Technology Bombay
Mumbai, India

Ramkumar Rajendran
Centre for Educational Technology
Indian Institute of Technology Bombay
Mumbai, India

Ritayan Mitra
Centre for Educational Technology
Indian Institute of Technology Bombay
Mumbai, India

ABSTRACT

Modern electrical grid systems demand engineers capable of adaptive reasoning, systematic justification, and principled decision-making under uncertainty. However, while many graduates excel technically, they often struggle with these expert-level competencies, revealing gaps in our understanding of expertise development. To address this, we need to identify the granular cognitive and epistemic shifts that occur along the expertise continuum. Drawing on Epistemic Frame Theory, this study examines how epistemic frames shape the developmental trajectory of expertise across second-year, third-year, and final-year undergraduates, compared against field professionals (experts). In the study, participants completed an open-ended electrical grid design task in a computer-based environment. We applied Min-Max normalization to verbal protocols to neutralize verbosity bias and reveal latent structural shifts. Our findings highlight a two fundamental developmental trajectories. An ascending trajectory captures the adoption of a professional lens, wherein students transition from academic idealism to professional pragmatism and from reactive debugging to proactive modeling. Conversely, a descending trajectory reflects the shedding of novice habits, indicating a gradual disengagement from surface-level and trial-and-error strategies. Notably, experts' strategic silence emerged as a marker of proficiency. We observed that experts' silence is a signal of proficiency. The high-frequency behaviors in novices, such as visual monitoring and explicit naming of components, fade away as knowledge becomes tacit. These findings suggest that expertise is defined as much by what is shed (novice habits) as what is acquired (professional lens). These insights suggest that engineering curricula should incorporate earlier authentic practice to bridge the theoretical trap fostering the transition from explicit theoretical rules to implicit professional norms.

Keywords

Epistemic Frame Theory, Trajectory of Expertise, Continuum of Expertise, Min-Max Normalization, Engineering Education

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1. INTRODUCTION

A purpose of formal education is to enable students to build domain-specific knowledge, ways of thinking, and professional practices that are essential for successful learning and to develop expertise in it [24, 28, 19]. The most important part is that expertise is not a general body of knowledge; it is grounded in numerous context-specific experiences. Expert knowledge is typically deeply tied to particular domains and develops through sustained participation in authentic practice [18]. The expertise acquired in a particular domain shapes professional expertise in that domain. [15]. Expertise is developed through progressive stages, with each stage characterized by qualitative transformations in how individuals perceive situations and make decisions [13, 20, 4, 27] [18].

The modeling of expertise through progressive stages is extensively discussed in foundational research, most notably in *the Dreyfus model of skill acquisition* [13], *the Benner mode* [4], *the Two expertise model* proposed by Hatano and Inagaki [27, 7]. *The skill acquisition model* proposed by Dreyfus and Dreyfus [13] is stage-based model, it conceptualize expertise as a progression through qualitatively distinct stages of novice, advanced beginner, competent, proficient and expert. This model emphasize changes in rule-following, intuition, and situational perception as individuals accumulate skills. Such models have been influential across professional domains. Benner [3] adapted Dreyfus' five-stage model of skill acquisition to nursing domain. Hatano and Inagaki [27], and later Carbonell in 2019 [7], differentiate between *routine experts* and *adaptive experts*. The routine experts are ones who perform efficiently in familiar situations and Adaptive Experts are who can transfer knowledge and creatively solve novel problems. Adaptive expertise builds on routine expertise, is shaped by task variety, and reflects a dynamic rather than static view of knowledge. Alongside the stage-based models of expertise, there are *cognitive theories* for problem solving strategies [9, 2, 34], *Mental models and situation awareness* that explain experts' superior anticipation of system behavior [22, 16] and *knowledge-based model* [15, 16, 17]. These existing models are predominantly cognitive, focusing on technical skills, social participation, and situational experiences.

Recent studies apply distinct theoretical lenses to understand the trajectory of professional development. Lyon [36] utilizes the Dreyfus model to structure the linear stages of teaching development in dental education. Dehn et al.[11] analyze the guided Self-Determination model, revealing the complex, multidimensional factors that drive skill acquisition beyond simple proficiency in nursing education. Furthermore, Kua et al.[32] examine Hatano's concept of adaptive expertise to highlight the necessity of cognitive flexibility in educational settings; they are specifically examining the epistemology. Although these models of expertise are useful for characterizing differences between novices and experts, they offer limited guidance for designing targeted interventions as they lack empirical evidence about when and how key transformations in expertise actually occur. Moreover, beyond cognitive dimensions such as skills and knowledge, existing models provide little clarity about which additional dimensions (e.g., identity, values, or professional judgment) contribute to more fine-grained developmental progressions.

This theoretical limitation is further compounded by a measurement challenge. As individuals develop expertise, what they choose to verbalize changes systematically. Empirical expert–novice studies show that experts often articulate fewer foundational concepts than novices because much of their domain knowledge becomes automated and tacit [1, 9, 34]. Consequently, traditional frequency-based analysis methods risk misinterpreting reduced verbalization as disengagement or conceptual weakness rather than recognizing it as a potential marker of proficiency. Addressing this issue requires both a multidimensional theoretical framework and analytical methods capable of this verbosity confound.

In this paper, we propose a multi-model expertise development, operationalized through Epistemic Frame Theory (EFT) [44, 42]. EFT conceptualizes a network of interconnected components, where individuals' engagement and practice within a community shape the development and organization of epistemic frames (Shaffer, 2006a). Epistemic frame theory suggests that every profession has unique collections of *Skills* (practical actions professionals perform), *Knowledge* (conceptual understanding professionals possess), *Values* (what are the believes of professionals and what they consider important), *Identity* (how professionals see themselves and their role), and *Epistemology* (how professionals justify decisions and determine valid reasoning) that construct an epistemic frame.

We move beyond simple usage counts to uncover the changing meaning of these epistemic frames. By applying Min-Max normalization to verbal protocols across four cohorts (second year, third year, final year, and a field professional), we neutralize verbosity bias to reveal two complementary developmental trajectories:

- Ascending Trajectories: The adoption of the professional lens
- Descending Trajectories: The shedding of novice habits

This developmental map provides a benchmark for designing stage-appropriate educational interventions. It identifies not only which expert-like behaviors emerge and should be reinforced through scaffolding, but also which persistent novice habits require explicit pedagogical attention to accelerate their decline. By revealing both what students must develop and what they must learn to abandon, this work enables educators to provide targeted support at the precise developmental moments when students need it most.

Understanding what students must develop alongside what they must shed enables educators to provide precisely timed support at critical developmental transitions. To empirically establish these ascending and descending trajectories, this study addresses two primary research questions:

1. What distinct developmental patterns emerge across the novice-to-expert continuum when epistemic codes are classified by their trajectory slopes?
2. How does the qualitative application of epistemic frames transform from second-year undergraduate students to practicing field professionals?

2. RELATED WORK

To understand how expertise develops, we must first understand what distinguishes experts from novices. Extensive research across multiple domains has documented systematic cognitive differences between expert and novice problem-solvers. Experts possess highly interconnected knowledge structures that support efficient chunking, reduce cognitive load. They can enable flexible, principle-based problem solving through forward reasoning and multiple solution pathways, along with extended reflection and evaluation [8, 9, 34, 50, 10, 39]. In contrast, novices rely on fragmented and superficial representations, they attend primarily to explicit problem features and known-unknowns rather than underlying principles, which limits transfer and strategy diversity [8, 9, 49, 40]. Novices predominantly employ means-end or backward inference strategies, resulting in trial-and-error approaches, minimal evaluation, and susceptibility to irrelevant information [34, 41, 26, 39, 38].

These expert-novice differences extend beyond problem solving. In categorization and representation tasks, experts emphasize deep structural relations while novices focus on surface or aesthetic features [25, 48, 31, 12]. This reflects the role of tacit, experience-based knowledge in expert performance—knowledge that novices have not yet developed.

However, this cognitive divide is not a static binary state. Research across domains demonstrates that the sharp distinctions between expert and novice represent endpoints of a developmental continuum rather than discrete categories. Expertise emerges through gradual, qualitative transformation. The Dreyfus model captures this progression well, describing a move from rigid, rule-based reasoning (Novice) to context-sensitive, situational understanding (Expert) [13]. Similar developmental stages characteristics have been noted in medicine, where expertise emerges through iterative refinement of pattern recognition [4]. Yet recognizing that expertise develops along a continuum raises a fundamental question: what, precisely, is developing?

Expertise is more than cognitive transformation; rather, it is fundamentally multidimensional. Epistemic Frame Theory proposes that professional expertise emerges through the integration of five interconnected dimensions: Skills, Knowledge, Values, Identity, and Epistemology (SKIVE) [42, 45]. These dimensions do not develop in isolation, but they integrate into a cohesive professional lens over time. For an engineer, a design decision is never purely technical. It represents an interplay between technical knowledge, identity as a problem-solver, and values regarding system reliability and societal impact [42]. This EFT-grounded perspective fundamentally reshapes how we must study expertise development: rather than tracking a single cognitive trajectory, we must examine how all five SKIVE dimensions evolve simultaneously—and potentially at different rates.

Understanding this multidimensional development has important practical implications. This multidimensional view helps explain why engineering graduates struggle in professional practice despite strong technical performance in coursework [46, 51]. The transition from student to professional requires transformation not only in knowledge and skills, but also in values, identity, and epistemology. Without all dimensions developing in coordination, individuals may possess technical competence yet lack the integrated professional judgment required for effective practice. Understanding how this multidimensional development unfolds raises critical questions.

How do these dimensions develop across the undergraduate journey? When do specific transformations occur? Do all dimensions develop at the same rate, or do some lag behind? Most critically, does expertise follow only an upward trajectory of acquisition, or does it also require the active shedding of novice behaviors? Answering these questions requires methodological approaches that can capture the activation of knowledge, values, and identity as students engage with authentic professional tasks.

Think-aloud protocols (TAPs) offer one such approach. TAPs have long served as the gold standard for examining cognitive processes in expert-novice research [**?**]. In engineering education, these protocols provide a rich verbal trace of how students at different levels navigate design tasks, identify hidden constraints, and justify their actions through professional norms. While traditional observation only records what a student do, think-aloud protocols reveal the why exposing the activation of specific epistemic frame elements during problem-solving. When enhanced by eye-tracking data (ET-RTA) [37], these protocols provide even deeper insight into the cognitive processes underlying professional reasoning.

However, possessing a methodological tool does not guarantee a complete developmental picture. Existing research has documented endpoints of the expertise continuum such as novice versus expert characteristics, but provides limited insight into the developmental stages between them. We lack detailed understanding of the specific transformations that occur at each year of undergraduate training. We do not know which dimensions develop early and which lag behind. Crucially, we do not know whether expertise development is purely acquisitional or whether it also involves the strategic abandonment of novice strategies. Without this granular developmental map showing both what students must gain and what they must shed, educators cannot design stage-appropriate interventions or provide targeted scaffolding at the precise moments students need support.

This study addresses this gap by revealing the bidirectional nature of expertise development across the undergraduate-to-professional continuum. Through a cross-sectional design comparing second-year, third-year, and final-year students with practicing professionals on an authentic engineering task, we created a detailed benchmark of developmental characteristics at each stage. This benchmark reveals not only what grows but also what must be shed—providing the complete picture needed to design effective, stage-appropriate educational interventions.

3. METHODOLOGY

3.1 Study Design and Participants

This study employs a cross-sectional research design to capture the developmental trajectory of expertise from the undergraduate to professional practice. The study was conducted with 15 electrical engineering undergraduate students categorized by their academic level: Second-Year (SE, n=6), Third-Year (TE, n=5), Final-Year (BE, n=4), and an industrial expert (Exp, n=1). The industrial expert has been working in the power system grid industry for more than 15 years. This distribution enables a granular comparison of epistemic frame shifts across key curricular milestones. All procedures were approved by the Institutional Review Board (IRB), and informed consent was obtained from all participants for the use of their behavioral and verbal data.

3.2 The "Power to the People" game

Present research utilized "Power to the People," (developed by (https://www.rhombicogames.com), a high-fidelity power system role-playing game. This game requires participants to manage complex grid operations like optimization, load balance, mitigating faults, etc., as load demand of city expand dynamically. This environment provides a rich context for process mining, as it forces participants to move beyond theoretical knowledge to professional application.

3.3 Data Collection Method

Data collection was structured into three distinct phases designed to ensure data validity and minimize the novelty effect of the game interface:

Orientation and Familiarization (30-45 mins): To ensure that subsequent data captured cognitive processes rather than interface-learning hurdles, participants underwent a standardized demo and checklist-driven practice. They practiced installing substations and managing generators in a neutral simulation environment ("Siem Reap, Cambodia").

Gameplay and Gaze Capture (30-40 mins): Participants transitioned to the experimental task centered on the "Agra, India" city layout. During this phase, a Tobii Pro Nano (60 Hz) eye tracker was used to record eye-gaze data. This eye-tracking layer serves as a digital trace of the participant's visual attention, providing a non-intrusive log of their interaction with the grid.

Eye-Gaze Enhanced Retrospective Think-Aloud (ET-RTA): Post-gameplay, we conducted structured interviews (average duration 70-80 minutes) using the ET-RTA protocol. Participants viewed their gameplay video overlaid with their gaze plots, which served as a cued-recall stimulus. This method allows the extraction of rich process level verbal protocols grounded in actual behavioral traces, reducing the risk of post-hoc rationalization [37].

3.4 Data Transformation and Coding

To bridge the gap between qualitative learning sciences and quantitative data mining, our approach treats unstructured verbal data as a source for computational modeling. This study employs a data processing pipeline that transforms coded verbalizations into normalized feature vectors. By calculating the slope of these vectors across academic cohorts, we establish a mathematical framework for mining the trajectories of expertise development. This methodology aligns with the EDM community's focus on modeling complex learner behavior through reproducible, quantitative metrics.

The recorded ET-RTA interviews were transcribed and analyzed using a hybrid coding approach. We employed the EFT framework deductively to categorize broad epistemic codes, while inductively deriving sub-codes like $S.Monitoring$, and $E.Real.Life$ etc. from the verbal data. The detailed codebook is available **here**. The reliability of coding was assessed using Cohen's kappa (κ) as a measure of inter-rater reliability. In the first round, two independent educational technology researchers coded 30% of the interview responses. This was followed by a second round of discussion to resolve disagreements and establish consensus. All codes demonstrated a high level of agreement between coders ($\kappa = 0.80$). This value indicates substantial inter-rater agreement [33] suggesting that the coding procedures were reliable across constructs.

The resulting dataset was normalized by calculating the relative frequency of codes per cohort (see section 4), enabling a quantitative analysis of the expertise trajectory, shifting the focus from qualitative description to data-driven pattern recognition.

4. ANALYSIS

To investigate the developmental trajectory of expertise, this study employs a cross-sectional quantitative design. By comparing four cohorts: second-year, third-year, and final-year undergraduate students, alongside practicing professional, we construct a developmental benchmarks representing distinct stages of professional growth. This approach allows us to identify patterns of expertise development across the undergraduate-to-professional continuum.

The challenge in analyzing the cross-sectional datasets is that code frequencies often exhibit extreme variance. Verbal protocols often generate massive amounts of unstructured data that are difficult to compare across different levels of expertise. A significant hurdle we encountered in this process was the natural variation in participant verbosity; for instance, a talkative novice might produce a higher raw frequency of codes than a concise expert, potentially skewing the developmental signal. In raw frequency analysis, the visual prominence of a code is strictly determined by its cumulative count [47]. This creates a visual flattening effect for lower-frequency codes. For example, if a skill code $.Troubleshooting$ appears 50 times and an epistemology code $E.Design$ appears 5 times, the graphs will be dominated by the skill code, and the visuals will be very flat for the epistemology code. In a standard line chart, the $S.Troubleshooting$ line will oscillate high on the Y-axis, whereas the $E.Design$ line, even if it triples from 2 to 6 mentions (a 200% growth), will appear as a nearly flat line at the bottom of the chart. One might visually conclude that nothing happened with the epistemology code, simply because its geometric slope is dwarfed by the magnitude of the skill code.

4.1 Two-Step Normalization Procedure

To enable fair comparison across cohorts despite both unequal sample sizes and scale differences, we employed a two-step normalization procedure.

Step 1: Group Averaging: To neutralize the influence of cohort size (SE=6, TE=5, BE=4, Exp=1), we first calculated group-averaged frequencies by $\bar{X}_{SE} = \sum X_{SE}/6$, $\bar{X}_{TE} = \sum X_{TE}/5$, $\bar{X}_{BE} = \sum X_{BE}/4$, and $\bar{X}_{Exp} = \sum X_{Exp}/1$. This yields a single representative value per code per stage.

Step 2: Min-Max Normalization: Even after group averaging, codes exhibit extreme variance in absolute magnitude (e.g., high-frequency $S.Troubleshooting$ vs. low-frequency $E.Design$.To address this, we applied standardization techniques such as min-max normalization to systematically transform these narratives into a quantifiable dataset. Min-max normalization as shown in equation 1 [21] standardizes the dataset, ensuring that all features contribute proportionately to the final result. By placing all data points on a common scale, we could exclude the impact of outliers on their broader conclusions [5, 47].

Let $C_{i,t}$ denote the averaged raw frequencies of code i at developmental stage t, where $t \in \{\mathrm{SE}, \mathrm{TE}, \mathrm{BE}, \mathrm{Exp}\}$. The normalized weight $W_{i,t}$ is calculated as:

$$W_{i,t} = \frac{C_{i,t} - \min(C_i)}{\max(C_i) - \min(C_i)} \tag{1}$$

where $\min(C_i)$ and $\max(C_i)$ represent the minimum and maximum frequencies of code i observed across the four temporal stages.

This transformation maps each code's emphasis to the unit interval $[0, 1]$. A value of 1 indicates the stage of maximum relative emphasis, while 0 indicates the minimum. By scaling the raw frequencies into a standardized range $[0, 1]$, we were able to conduct a fair comparison of all the code elements across the second-year (SE), third-year (TE), final-year (BE), and expert groups, regardless of their total word count. This mathematical adjustment was central to our study, as it enabled us to visualize and quantify the movement of expertise. Specifically, it allowed us to model the expertise continuum as a series of developmental trajectories. The normalized values of all the codes helped us to plot the trajectories of all the codes as shown in Figure 1.

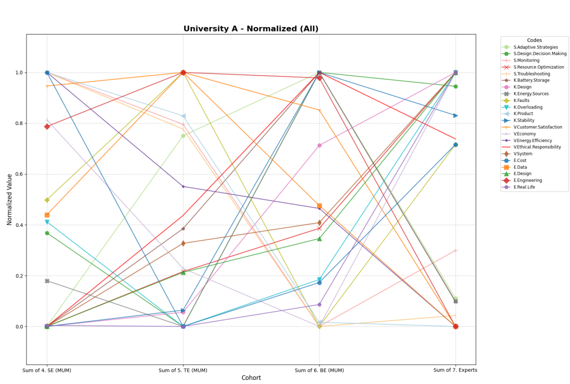

Figure 1: Developmental Trajectories of epistemic codes using min-max normalization

4.2 Slope

Figure 1 shows the trajectories of all the codes across cohorts, but to quantify the directional magnitude of each code, we derived a slope for each trajectory. This slope represents the mean rate of shift from the novice state (SE) to the expert state (Exp). Given that the timeline consists of four distinct stages (SE, TE, BE, Exp), the slope is defined as the total normalized displacement averaged over the temporal span:

$$\lambda_i = \frac{W_{i,\text{Exp}} - W_{i,\text{SE}}}{3} \tag{2}$$

The resulting λ_i values range from -0.33 (a complete shift from maximum usage at SE to minimum usage at Expert) to $+0.33$ (the inverse). The overall range of the λ_i values is therefore 0.66.

4.3 Statistical Thresholding and Classification

To categorize the diverse trajectories into meaningful epistemic patterns, we established a slope-based threshold τ to distinguish substantive developmental trends from transitional volatility.

An analysis of the distribution of slopes across the combined dataset for all $N = 44$ across 22 unique codes revealed a mean of $\mu = 0.02$ and a standard deviation of $sd = 0.24$. To ensure robustness in identifying distinct developmental trajectories, we selected a threshold of $\tau = \pm 0.15$, derived from the data distribution and focused on quartile alignment (see Figure 2). Specifically, this threshold approximates the absolute boundaries of the interquartile range (IQR = 0.42, spanning Q1 ≈ -0.17 to Q3 $\approx +0.25$): the negative threshold (-0.15) is close to Q1 (capturing the lower quartile's tail for negative shifts), while the positive threshold ($+0.15$) falls between the median (Q2 ≈ 0.02) and Q3 (highlighting the upper quartile for positive shifts). This approach effectively filters out central noise within the IQR, ensuring the classification prioritizes the most pronounced shifts in the outer quartiles while accounting for the distribution's slight positive skew.

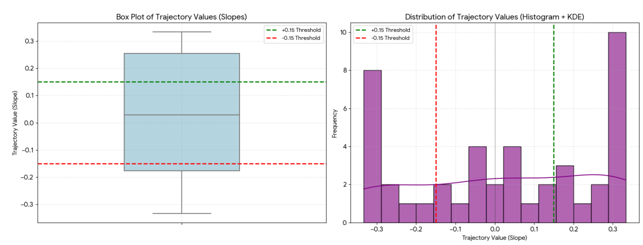

Figure 2: Statistical distribution of trajectory slopes (λ) for all codes. (Left) Box plot displaying the Interquartile Range (IQR) with Q1 ≈ -0.17 and Q3 ≈ 0.24. The dashed lines at ± 0.15 align closely with these quartiles, justifying their use as discriminatory thresholds. (Right) Histogram. The red (-0.15) and green ($+0.15$) thresholds clearly separate the central "transitional" bell curve from the significant negative and positive tails (Major Decline and Major Growth).

Using $\tau = 0.15$, we categorized the epistemic trajectories into four distinct types as shown in Table 1.

Table 1: Threshold Value Range for Categorizing Trajectory Types

Trajectory Type	Mathematical Definition
Type 1: Major Growth	$\lambda_i > +0.15$
Type 2: Minor Growth	$0 < \lambda_i \leq +0.15$
Type 3: Minor Decline	$-0.15 \leq \lambda_i < 0$
Type 4: Major Decline	$\lambda_i < -0.15$

4.4 Integration of Qualitative Protocol

To interpret the trajectories derived from the slope-based classification, we employed a qualitative approach. While the quantitative metrics (slope λ) identify which behaviors change, they do not explain how the nature of that behavior transforms. Therefore, we aligned the normalized code weights (W_i) with their corresponding verbal protocol segments. For each significant trajectory, we conducted a thematic analysis of the excerpts to extract the semantic and cognitive shifts driving the statistical trend, ensuring that every quantitative claim is grounded in participant evidence.

5. RESULTS

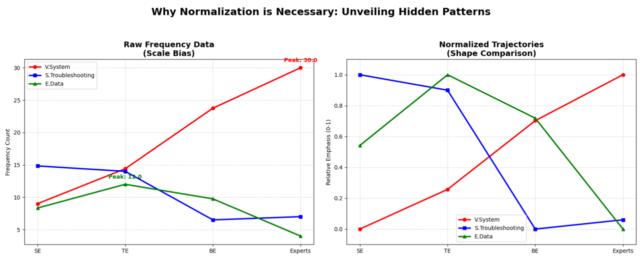

Figure 3: Comparative plots of raw frequency (left) and normalized trajectories (right) for selected codes: V.System, S.Troubleshooting, and E.Data.

To illustrate how normalization helps visualize epistemic trajectories, we compare the raw and normalized distributions of three representative codes: $V.System$ (Values: System Stability), $S.Troubleshooting$ (Skills: Troubleshooting), and $E.Data$ (Epistemology: Data-driven Justification) (Figure 3). The raw frequency graph (left) exhibits a significant scale bias, where high-volume codes like $V.System$ (RED) peaking at ≈ 30, exerts a magnitude bias that suppresses lower-frequency codes like $E.Data$ (GREEN). $E.Data$ is less frequent peaking at ≈ 12 and appears flat across the four cohorts. If we have to make the inference from this, the development across the 4 cohorts will be stagnant when viewed on a shared raw axis with $V.System$.

In contrast, the min-max normalized graph (right) performs a crucial analytical equalization. By scaling each trajectory independently to a standardized $[0, 1]$ range, we eliminate verbosity-induced noise and reveal the relative intensity of each epistemic element within its own developmental lifecycle. This transformation allows the trajectories' distinct shapes to emerge as the primary visual feature. We can now observe, for instance, that while $S.Troubleshooting$ (BLUE) might have a high raw volume in the sophomore year, its relative importance to the expert's frame is negligible compared to the sharp uptrend of $E.Data$. Without this normalization, our analysis would be trapped in a frequency bias, leading to erroneous conclusions. Such as certain professional traits are absent simply because they are spoken with more precision and fewer words. Normalization thus serves as a lens that brings the structure of the epistemic frame into focus, allowing us to quantify the movement of expertise across the continuum with mathematical parity.

5.1 RQ1

What distinct developmental patterns emerge across the novice-to-expert continuum when epistemic codes are classified by their trajectory slopes?

Following the application of min-max normalization, we performed a slope-based classification to categorize the developmental trends across 22 codes. Utilizing the thresholds defined in Table 1, four major trajectories of the movement of epistemic frames across the four cohorts emerged. These trajectories are linear (Type 1: Major Growth; Type 4: Major Decline) and non-linear (Type 2: Minor Growth; Type 3: Minor Decline) (Figure 4.)

The sequence of normalized weights W_i corresponding to each trajectory is presented in Table 2.

Table 2: Sequence of the SE, TE, BE, Exp weights in four trajectories

Trajectory Type	Sequence of normalized weights	Shape of the Trajectory
Type 1: Major-Growth	$W_{\text{SE}} < W_{\text{TE}} < W_{\text{BE}} < W_{\text{Expert}}$	Uptrend
Type 2: Minor-Growth	$W_{\text{SE}} < W_{\text{TE}} \leq W_{\text{BE}} > W_{\text{Expert}}$	Hump
Type 3: Minor-Decline	$W_{\text{SE}} > W_{\text{TE}} \geq W_{\text{BE}} < W_{\text{Expert}}$	Dip
Type 4: Major-Decline	$W_{\text{SE}} > W_{\text{TE}} > W_{\text{BE}} > W_{\text{Expert}}$	Downtrend

In this paper, we focus our analysis exclusively on the two most significant graphs: *Type 1 (Major Growth)* and *Type 4 (Major Decline)*. Type 1 (Major Growth: Uptrend): These trajectories represent "expert-like" competencies that show a consistent increase in relative intensity as students move toward professional practice. Type 4 (major Decline: Downtrend): These trajectories represent "novice-heavy" habits that are systematically abandoned or automated as expertise develops.

We have intentionally excluded Type 2 and Type 3 from the current discussion. These categories exhibit high intra-group volatility, characterized by non-linear fluctuations such as "humps" (peaks at TE or BE) and "dips" (Dips at TE or BE). In the context of trajectory modeling, these volatile patterns often contain a high degree of statistical noise or represent complex, intermediate cognitive restructuring that requires a more granular longitudinal analysis. Therefore, the detailed examination of these fluctuating patterns is beyond the scope of this paper.

5.2 RQ2

How does the qualitative nature of epistemic frames evolve from Second-Year students to practicing professionals?

This section talks about the two primary developmental trajectories: *Type 1 (Major Growth)* and *Type 4 (Major Decline)* revealed through the application of min-max normalization and slope-based classification. For each trajectory, we present the quantitative findings followed by a qualitative analysis of representative excerpts. This mixed-methods structure allows us to demonstrate not only the statistical magnitude (through W_i) of the change but also the qualitative evolution of the learner's reasoning strategies from the Second Year (SE) to the Expert level.

5.2.1 Type 1: Major Growth: Uptrend

Figure 5 shows the type 1 trajectory with the slope $\lambda \geq +0.15$. This Trajectory represents the acquisition of high-level professional frames. The key codes that are under are:

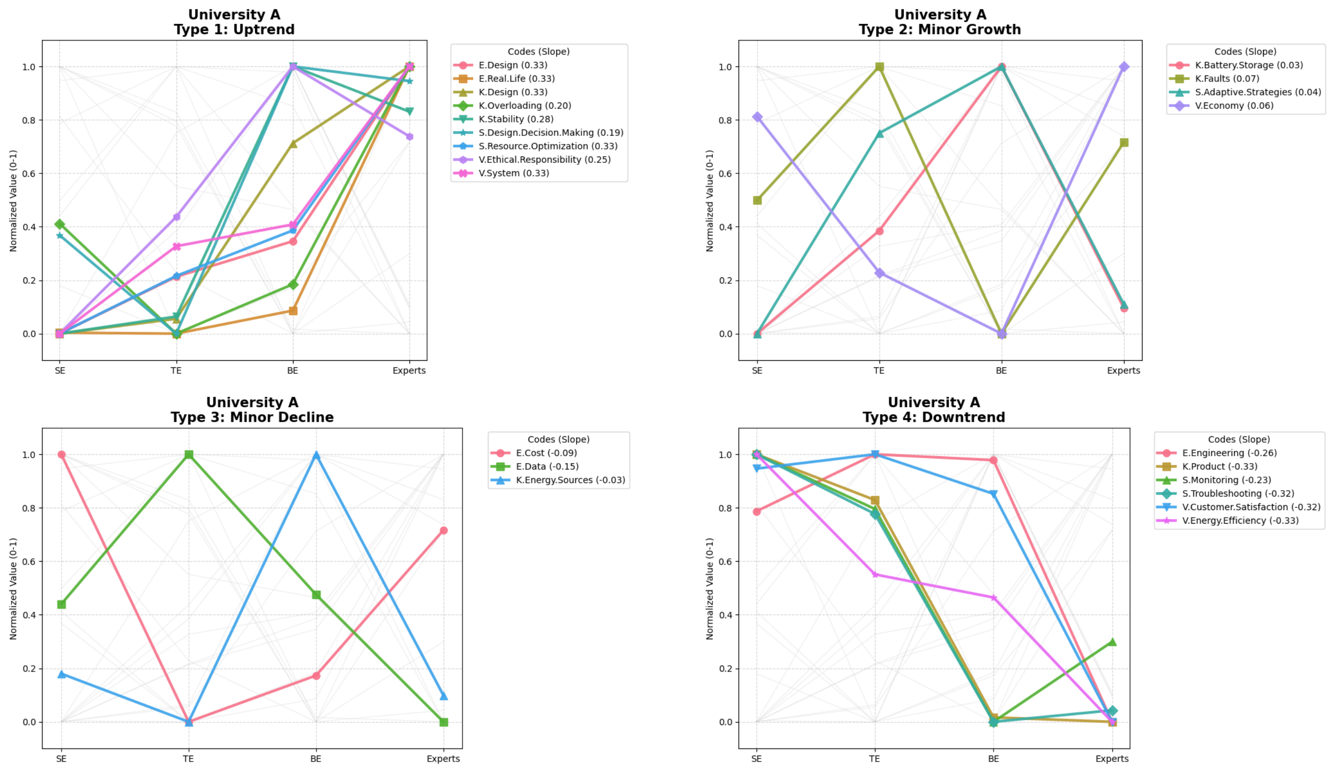

Figure 4: Classification of trajectories into four types with respect to slope threshold (± 0.15).

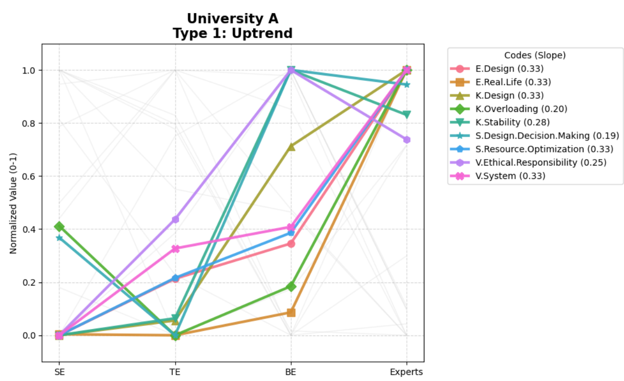

Figure 5: The Ascending Trajectory of epistemic frames with $\lambda \geq +0.15$.

- E.Design: 0.33
- E.Real.life: 0.33
- K.Design: 0.33
- K.Overloading: 0.20
- K.Stability: 0.28
- S.Design.Decision.Making: 0.19
- S.Resource.Optimization: 0.33
- V.Ethical.Responsibility: 0.25
- V.System: 0.33

These codes exhibit a consistent increase in normalized weight from the Second Year (SE) to the Expert (EXP). The sequence of the weights W_i for this Type 1 trajectory can be seen Table 2 in row 1, signaling the successful adoption of the learner into the community of practice.

$E.Real.Life$ ($\lambda = 0.33$): It is the most significant developmental signal observed in Uptrend. The trajectory reveals a late-blooming pattern where the code is virtually flat in SE (0.0) and TE (0.12) cohorts, reflecting an academic isolation where real-world constraints are invisible to the student. A noticeable shift occurs in the BE cohort (0.58), but the Expert cohort reaches saturation (1.0). Qualitative analysis shows that Experts exclusively use field heuristics. Experts replace theoretical citations with professional intuition. As one expert noted, *"In a real grid, you utilize diversity factors... you don't design for the peak of every single house simultaneously."*. This expert behavior shows the effective replacement of the classroom lens of the novice with the field lens of the practitioner.

$S.Design.Decision.Making$ ($\lambda = 0.19$): This epistemological shift is mirrored in the evolution of design logic, revealing a four-stage maturation moving from surface heuristics to deep structural analysis. Novices (SE) initially relied on cost and quality heuristics, operating on the naive assumption that price equals quality. As one student noted, *"I thought the more expensive the thing, the better. So I bought it... I thought it would be better if the cost was higher."* This indicates a decision-making process driven by budget variables rather than technical fit. By the Third Year (TE), this evolves into Attribute Matching, where students align static component features with spatial needs. For instance, a TE student stated, *"...because this city is small. So I have used a small local substation."* While logical, this approach remains static and spatial. A higher-order complexity emerges in the Final Year (BE), characterized by Multi-Variable Analysis. These students balance conflicting variables like terrain, weather data, and future load before execution. An excerpt illustrates this data-driven approach: *"I looked at precipitation graphs... we have a lot of precipitation... I looked at the terrain where I can see that there are some places where we have trees."* Finally, Experts transcend the game's explicit variables to incorporate Real-World constraints that are invisible in the game interface. They describe the grid's topology before placing a single component, noting, *"First, I am identifying the load centers... the ring main unit will provide redundancy here before I even connect the generation."* The expert protocol reveals a distinct pre-design phase absent in novices, in which contingencies for future load growth are calculated before implementation.

V.System ($\lambda = 0.33$):The data further highlights a transformation in how participants define value, specifically capturing the prioritization of grid stability. In the SE cohort, this value appeared frequently but was framed negatively in terms of the avoidance of game penalties, with students noting, "I removed the line because the message came." By the Expert phase, the normalized frequency remained high, but the definition of the system changed from a set of game rules to an internalized standard of care. They impose an intrinsic benchmark of system health that dictates grid robustness, regardless of whether the external agent explicitly penalizes them or not. An expert illustrates this internalized standard, stating, "I try to keep the system healthy... If there is a breakdown, how to restore it immediately, how to stay healthy, we work from this perspective..." This reflects a shift in role identity from a builder following instructions to a guardian of continuity.

V.Ethical.Responsibility ($\lambda = 0.25$): Concurrently, this trajectory tracks the expansion of the moral boundary. Novices (0.20) framed ethics transactionally, viewing the utility to customer relationship as a commercial contract for profit. One SE student explicitly stated, *"ofcourse, Customer satisfaction is my priority... if I promise that I will give this to customers, I will give it first... that will give me profit..."* This perspective shifts toward environmental stewardship in the Final Year (BE). These students are willing to sacrifice economic efficiency to protect the aesthetic and environmental integrity of the region. A final-year student noted, *"Also coal... of course it's cost is less, but over the longer period of time it will get extinct. And also there will be a lot of pollution and if this polluted air gets to Taj Mahal of course there will be consequences to its beauty..."* Finally, values shift to a non-negotiable civic duty for Experts (1.0), who feel it is the fundamental purpose of their profession. The expert views the grid not as a commercial asset, but as a public utility essential for life. Stripping away all complex variables, one expert revealed the singular mission of the grid: *"We just want the system to deliver electricity to every consumer. That's all we want. We work from this perspective."*

This indicates that universal accessibility is the foundational axiom of their mental model, creating an obligation to serve everyone regardless of difficulty.

S.Resource.Optimization ($\lambda = 0.33$): Finally, this trajectory tracks the sophistication of efficiency strategies. SE novices employed naive spatial symmetry, such as "splitting the load 50/50" based purely on visual geometry. One SE student explained, *"I will give an even distribution. If there are 100 residents, 50 will be distributed by one line and 50 by another line. So that the load on the line will be less. I have split it like that."*. TE students advanced to component-level optimization (e.g., matching a small substation to a small city), reflecting a textbook understanding of capacity. However, the trajectory peaks as Experts integrate complex variables—cost, line loss, and future demand—into a single decision matrix. Experts demonstrate a well-thought-out optimized system, with reasoning well grounded in real-world practices. Continuously reflecting on field experience, an expert noted, *"The installed capacity must be higher than the requirement. So, I was thinking of the maximum install capacity power plant...I learned from that practical experience that segregation of equal loading is very much insufficient."*

5.2.2 Type 4: Major Decline: Downtrend

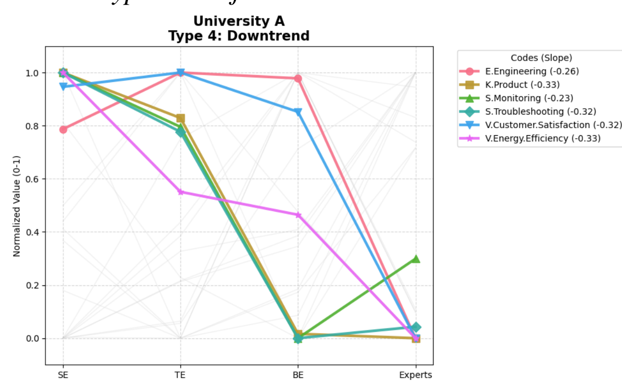

Figure 6: The Descending Trajectories of Cognitive Automation ($\lambda \leq -0.15$)

Figure 6 shows the type 4 trajectory with the slope $\lambda \leq -0.15$. This trajectory represents the fading away of the novice habits. The sequence of the weights W_i for this Type 4 trajectory can be seen Table 2 in row 4. This decrease in weights W_i are critical as they identify behaviors that are prominent in novices(SE) but recede as expertise develops (Exp). This trend does not indicate skill loss, but rather the *cognitive automation* of foundational processes.

The Type 4 trajectories ($\lambda \leq -0.15$) exhibited a negative slope. The key codes fall under:

- S.Troubleshooting (-0.32)
- S.Monitoring (-0.23)
- V.Customer.Satisfaction (-0.32)
- K.Product (-0.33)
- V.Energy.Efficiency (-0.33)

- E.Engineering (-0.26)

S.Monitoring ($\lambda = -0.23$):The most dramatic decline was observed in this trajectory, which captures the reliance on visual verification. SE participants recorded the highest weight (1.0), primarily associated with surface monitoring (constantly scanning the interface for color-coded warnings). An SE student noted, *"I am checking the red line... it turned red again."* This reflects a reactive stance where the student awaits visual feedback from the game mechanics to validate the grid's state. In contrast, Experts (< 0.1), possessing a proactive mental model. Experts analyse the load distribution internally before placement. Consequently, the need for explicit verbal monitoring vanishes; they trust their internal simulation, whereas the novice requires constant external validation.

S.Troubleshooting ($\lambda = -0.32$): Similarly, this trajectory tracks the shift from a trial-and-error loop of patching crashes to a proactive design strategy. Novices (SE) explicitly described a reactive dependency on game notifications, stating, "I got the message twice. I removed them as the message came... Because the last time was short circuit. I wish there was a help button... I thought I was doing it wrong and that's why he is giving me notice." When Third-Year (TE) students encounter errors, they understand the underlying reasons but still perform actions strictly by the rules, indicating a transitional learning phase. A qualitative leap occurs in the Final Year (BE), where students stop reactive error fixing and start simulating alternative strategies to prevent errors entirely. As one BE student explained, "I would have added wind turbine if there was some height. this is like, you know, just alternative way..." This marks the transition to a proactive design strategy that resolves contingencies upfront, eliminating the need for reactive fixes.

The interesting finding for this code is, as expertise develops, this code vanishes. In opposition to the students, the Expert starts designing the grid for reliability and, as they do so, accounts for contingencies. The contingency-oriented behavior can be seen through *"..whatever the fault occurs further, lets say this point, is prone to the overloading, we can have one fault, but as I have this one substation, it is backup for me. So that I can distribute power properly or evenly to particular area. . . "*. This expert's behavior is typically because they employ a well-thought-out plan in advance.

K.Product ($\lambda = -0.33$):A similar trend characterizes a shift from declarative labeling to tacit integration. The data shows a monotonic decline from SE (1.0) to Expert (0.0). SEs record the highest weight because they must explicitly verbalize their understanding of surface features, often appearing overwhelmed by game mechanics. An SE student noted, *"...I chose a wind turbine, but I didn't get the output. . . I thought maybe it's a problem with wind or connection maybe..."* This excerpt highlights a focus on the object itself rather than the underlying reason for its failure. In the intermediate phases, the nature of knowledge becomes procedural. While TEs and BEs still frequently reference product names, they begin to connect these labels to broader concepts, attaching conditions and rules to facts. They select objects based on specific conditions rather than just availability. The Expert, conversely, invokes the tacit professional world—referencing concepts like Site Survey and Load Center—that precedes the product. The quantitative drop signifies that the game interface has become transparent; they think through the component to the solution. For the professional, the wind turbine is not a standalone object to be bought, but a conditional solution that emerges from a rigorous assessment. As one expert explained, *"So, in real life, there are many more constraints... we do site survey, we do load center survey... If it is in hilly areas, with good wind speed, we go for wind power turbines... If it is near to the coal mines... we go for coal..."* The expert zooms out beyond the game graph to reference the site survey protocol.

E.Engineering ($\lambda = -0.21$): An interesting deviation from the linear downtrend was found in this trajectory, which followed an inverted-U shape. It peaked in the Third Year (TE) (1.0), reflecting a cohort immersed in heavy theory ("Power Systems I"). TEs attempted to force complex academic constraints, such as per-unit systems or reactance values, onto the game to validate their knowledge. As one TE student noted, *"I was thinking about the 'per-unit' system... to see if the game follows the standard reactance values."* Strikingly, the Expert cohort dropped to zero. Experts did not cite academic theories, voltage or current Laws, or even Electricity Rules by competent authorities, because these norms are internalized and hence tacit. This finding suggests a theoretical trap in the TE year that must be transcended to achieve professional fluency.

V.Energy.Efficiency ($\lambda = -0.33$) along with *V.Customer. Satisfaction* ($\lambda = -0.22$): Lastly, value-based codes showed marked declines. Novices verbalized these as distinct, affective goals, often worrying about "sad people" or "happy faces" on the interface. For experts, these are not separate values to be maximized but embedded constraints within the primary goal of *V.System*; they do not speak of efficiency separately because a stable grid is inherently efficient. The disappearance of these explicit codes marks the transition from explicit student values to implicit professional norms.

6. DISCUSSION

This study aimed to map the granular developmental trajectory of electrical engineering expertise. By quantifying the shift in epistemic frames from the Second Year (SE) to the Expert level, our results provide the empirical evidence for the traditional accumulation model of expertise. The data reveals that expertise development is not merely a linear addition of technical skills, but a complex, trajectories: the simultaneous Adoption of a Professional Lens (Ascending Trajectories) and the Shedding of Novice Habits (Descending Trajectories). This section discusses the mechanisms driving these patterns.

6.1 Adoption of a Professional Lens: Game Rules to Professional lens

The ascending trajectories of *E.Real.Life* and *V.System* illustrate a fundamental shift in the learner's Locus of Control. Novices (SE) operate within an academic frame, where value is defined externally by game mechanics or grading rubrics. This aligns with Engstrom's [14] distinction between school-going activity, where the object is the grade, and work activity, where the object is the societal value.

Their high frequency of *V.System* indicates a defensive mechanism, they act to avoid error messages rather than to ensure system health.

In contrast, the Expert frame is driven by an Internalized Standards. The synchronization of *V.System* and *V.Ethical. Responsibility* in the expert cohort suggests that for a professional, technical decisions are inseparable from their social consequences. This confirms Shaffer's [44] core tenet that professional expertise is not just "knowing how" (Skills) or "knowing that" (Knowledge), but "knowing with" adopting the values and identity of the community of practice. This trajectory reflects Lave and Wenger's [35] theory of Legitimate Peripheral Participation: novices remain on the periphery of the engineering community, engaging academic problems without context, while experts demonstrate full participation through internalized professional values and identity. The delayed emergence of *V.Ethical.Responsibility* codes suggests that undergraduate curricula provide limited opportunity for authentic engagement with the community of practice where these dimensions are enacted [52]. The delayed emergence of these codes points to a critical gap in the curriculum. While students acquire technical competence early, they suffer from contextual isolation, lacking the situated learning environment described by Lave and Wenger [35]. They possess the syntax of engineering (the math) without the semantics (the professional meaning). The sharp rise in the Expert cohort confirms that true fluency requires the adoption of this professional lens. This is a process that currently appears to happen largely after the graduation.

6.2 Shedding Novice Habits: From Reactive Monitoring to Proactive Design

The steep decline in *S.Monitoring* and *K.Product* highlights the mechanism of how novices display a high interaction with game interface, constantly verbalizing labels and verifying visual feedback from the system. They constantly verbalize component labels and verify visual feedback, outsourcing working memory to external representations—a phenomenon known in cognitive science as distributed cognition [29]. This external scaffolding is necessary and adaptive at early stages; without robust internal models, novices require the interface to confirm their understanding at each step.

However, the persistence of these behaviors in third-year (TE) and final-year (BE) students signals problematic dependency. This reflects what Braver [6] terms reactive control: students respond to feedback rather than anticipating consequences beforehand. They rely on the interface to tell them whether a design works, treating error messages as cues to act upon rather than using principled reasoning to avoid errors in the first place. While *S.Design* was visible in their protocols, it lacked correlation with *K.Design* and *E.Design* novices were mimicking engineering actions without the supporting epistemic structure to predict outcomes.

In contrast, experts demonstrate proactive control [6, 30], they simulate outcomes internally before acting. The expert's relative silence during problem-solving is not an absence of cognition but evidence of internalized mental models. The epistemic frame has become so compressed that intermediate reasoning steps no longer require conscious verbalization or external verification. Experts have effectively shed the scaffolding behaviors that once supported their learning, achieving what Dreyfus and Dreyfus [13] describe as the fluid, intuitive performance of expertise—no longer relying on context-free rules or external feedback but on internalized professional judgment.

6.3 The "Theoretical Frame": The Intermediate Effect

An interesting finding was the trajectory of *E.Engineering*, which peaked in the Third Year (TE). This aligns with the intermediate effects observed in medical education by Schmidt and Rikers [43], where intermediate learners process information more laboriously than both novices and experts due to the activation of elaborate but encapsulated causal networks. The TE cohort, immersed in heavy theory courses, attempted to force rigid academic abstractions e.g., $(Per - UnitSystems)$ onto a dynamic problem where they were ill-suited. This represents rigidity of the academic, as there is more emphasis on theoretical precision (*E.Engineering*) that temporarily overrides practical intuition (*E.Real.Life*). If not corrected, this leads to graduates who are technically rigorous but practically paralyzed. The drop to near-zero in the expert cohort confirms Glaser's [23] observation that expertise relies on flexible, context-sensitive heuristics rather than the rigid application of weak methods.

6.4 The Expert as Benchmark

A key methodological consideration in this study concerns the asymmetric sample composition, particularly the inclusion of a single expert participant. While this represents a limitation in terms of statistical generalizability, the design employs the expert not as a representative mean but as "a gold standard benchmark". This methodological approach aligned with Epistemic Frame Theory's use of professional exemplars to define the target epistemic state toward which learners progress [44]. This benchmark serves to identify the "ceiling" of the professional lens, establishing the developmental endpoint against which student trajectories can be mapped.

The resulting trajectories reveal systematic patterns: ascending codes (e.g., *E.Real.Life*, *V.Ethical*) show consistent growth from SE through Expert, while descending codes (e.g., *S.Monitoring*, *K.Product*) demonstrate systematic decline. These patterns emerge not from statistical aggregation across multiple experts, but from the structural positioning of student cohorts relative to the professional benchmark. The consistency of these trajectories across multiple SKIVE dimensions—with some ascending, some descending, and some exhibiting non-linear patterns—suggests that the observed trends reflect genuine developmental phenomena rather than artifacts of individual expert variation.

7. CONCLUSION AND IMPLICATIONS

This study highlights the holistic nature of the expertise gap: students do not primarily lack knowledge; rather, they operate within a fractured epistemic frame in which theory, design, and ethics are treated as separable academic tasks. In contrast, expert practice reflects a comprehensive epistemic frame, in which technical reasoning, ethical judgment, and contextual awareness are inseparable and enacted simultaneously through an internalized professional lens. By applying min-max normalization to verbal protocols, we effectively neutralized the verbosity bias that often obscures qualitative comparisons. This methodological innovation allowed us to visualize expertise as two simultaneous trajectories: the *Adoption of Professional lens* (Uptrends) and the *Shedding of Novice Habits* (Downtrends). Our analysis confirms that the silence of an expert is as significant as the speech of a novice. The monotonic decline of codes like *K.Product* and *S.Monitoring* provides empirical evidence that expertise involves the internalization of rules. Conversely, the ascent of *E.Real.Life* and *V.System* maps the transition from a reactive, rule-based game lens to a proactive, ethical field lens.

The revealed trajectories provide actionable insights for curriculum design, specifically for bridging the gap between academic theory and professional practice. The late emergence of *E.Real.Life* suggests that current curricula may isolate students in academic idealism for too long. To accelerate novices' development toward expert-like competencies, programs should integrate real-world constraints. The trajectory of *V.Ethical.Responsibility* implies that ethics training must evolve. Rather than treating ethics as a separate compliance module, it should be embedded in technical design tasks.

8. LIMITATIONS AND FUTURE WORK

We acknowledge that the single-expert (n=1) limits claims about variability in expert performance across engineering sub-domains or institutional contexts. Future work should expand the expert cohort to examine whether these trajectory slopes remain stable across diverse professional populations. Such expansion would enable investigation of whether the professional lens exhibits domain-specific variations or represents a more universal engineering epistemic frame. Nevertheless, the current benchmark approach provides sufficient granularity to identify which expert-like competencies emerge at which undergraduate stages and which novice behaviors require explicit intervention—actionable insights that inform curriculum design even in the absence of expert population statistics.

Additionally, the cross-sectional design infers developmental trajectories rather than tracking them directly. Future research should employ longitudinal designs to validate whether individual learners typically traverse these inferred paths. Furthermore, to empirically triangulate the phenomenon of "expert silence" (specifically in *S.Monitoring*), future work will integrate Multimodal Learning Analytics (MMLA).

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