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Timing as Signal: Submission Hour as a Predictor of Academic Performance in an Engineering Design Module

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ABSTRACT

Learning management systems record the exact time students submit their work, yet this behavioral trace is rarely used to examine student performance. This study investigated whether the hour at which a student submits the most technically demanding formative assessment in an engineering design module predicts both that assignment mark and the final module outcome. Data were drawn from three consecutive cohorts (2023–2025) of students enrolled in Design Project III, a Level 6 module at the Central University of Technology, Free State, South Africa. Submission timestamps for 387 student-year records were extracted from the Blackboard Learning Management System and classified into four deadline-day time bands. Statistical analysis revealed a significant negative relationship between submission hour and Submission 2 mark (Pearson $r = -0.21$, $p < .001$), with students who submitted in the last hour (16:00–17:00) scoring a mean of 54.32% compared with 64.22% for morning submitters (a gap of 9.9 percentage points). This effect carried through to the final module mark ($r =-0.15$, $p = .003$). Critically, no comparable effect was found at the summative final submission ($p =.619$), confirming that the relationship is specific to the intermediate, high-complexity assessment stage. These findings suggest that submission timing may serve as a practical early warning indicator of academic risk in engineering design modules.

***Keywords**: academic procrastination, learning analytics, engineering education, self-regulated learning, submission behavior*

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INTRODUCTION

“The data generated by students as they interact with educational software can be analyzed to improve both learning and the systems that support it” (Baker & Inventado, 2014). This is especially relevant in engineering education, since learning management systems (LMSs, digital platforms used to manage course content, assignments, and student submissions) now generate exactly this kind of data, in the form of detailed, timestamped records of student behavior. These records offer a largely untapped opportunity to examine what students do and when, and how this relates to their academic performance.

Engineering programs at universities of

technology must produce graduates who are both technically competent and professionally responsible. The Engineering Council of South Africa (ECSA) is the statutory body responsible for engineering accreditation in South Africa, and its Graduate Attribute 10 explicitly links engineering professionalism to behaviors such as the timely submission of work (ECSA, 2019). As outcomes-based and continuous assessment approaches become standard in engineering curricula, the institutional data they generate are well suited to behavioral analysis that supports both teaching and learning (Hlosta et al., 2022).

Research consistently shows that delaying task completion is negatively associated with academic performance, and that this relationship is strongest when tasks are complex and demanding (Balkis & Duru, 2016; Honicke et al., 2023; Steel, 2007). Learning analytics researchers have begun to operationalize this through submission timestamps extracted from learning management systems (Lotz et al., 2022; Tempelaar et al., 2020). However, most studies have examined assignment submission timing in general terms, without asking whether the effect differs between assessment stages that vary in cognitive and technical difficulty. That question, whether timing matters more at some assessment stages than others, remains unanswered in the engineering education literature (Broadbent & Poon, 2015; Lim et al., 2021).

The aim of this study is to determine whether the hour at which a student submits the most technically demanding formative assessment in an engineering design module predicts both that assignment mark and the final module outcome. A further aim is to determine whether any such effect is specific to that assessment stage.

The remainder of this article is organized as follows. The Literature Review examines prior work on self-regulated learning, academic procrastination, and learning analytics. The Study context describes the institution, program, and module. The methodology details the research design, data sources, and statistical procedures. The results section presents the statistical findings. The discussion interprets these findings and addresses limitations. The conclusion summarizes the contribution and offers practical recommendations.

LITERATURE REVIEW

Three bodies of knowledge inform this study: theories of self-regulated learning, research on academic procrastination, and the emerging discipline of learning analytics in higher education.

Self-regulated learning (SRL), the process by which students actively plan, monitor, and evaluate their own effort, explains why some students manage complex tasks more successfully than others. Zimmerman’s model identifies planning, monitoring, and self-evaluation as the core processes through which students regulate their effort (Zimmerman, 2000). Pintrich extended this to include motivational regulation, showing that students who start work early and sustain engagement through a project tend to perform better (Pintrich, 2004). Research across tertiary settings has consistently confirmed this relationship, particularly in project-based and design-oriented curricula (Broadbent & Poon, 2015; Panadero, 2017). In engineering education specifically, Lim et al. (2021) found that SRL strategies predicted performance even after controlling for prior achievement, suggesting that the ability to manage one's own learning process is an independent driver of success.

Academic procrastination, which is defined as voluntarily delaying tasks despite knowing the consequences, has been studied extensively since Steel's (2007) landmark meta-analysis, which found a consistent negative relationship between procrastination and performance across hundreds of studies ($r = -0.19$ to -0.28) (Steel, 2007). The effect is stronger when tasks are more complex (Balkis & Duru, 2016; Kim & Seo, 2015). In engineering design, this distinction matters because assignments within the same module can vary considerably in technical demand. Klassen et al. (2008) showed that students who submitted near deadlines also tended to report lower confidence in their own abilities, suggesting that late submission reflects not just poor time management, but a deeper uncertainty about the quality of the work (Klassen et al., 2008). These behavioral patterns align naturally with what submission timestamps can reveal.

Learning analytics has made it possible to measure engagement and procrastination through system-generated data rather than self-report. Hlosta et al. (2022) demonstrated that predictive learning analytics systems applied to virtual learning environment data can improve teacher practice and student outcomes in online STEM disciplines, while also showing that model errors are systematically linked to unexpected student circumstances not captured in the submission record. Arizmendi et al. (2023) demonstrated through a comprehensive review that LMS digital trace data (including submission timing and engagement frequency) predicts for-credit course performance with meaningful accuracy, adding explanatory value beyond demographic and prior achievement data alone. Lotz et al. (2022) investigated submission timing in an engineering cohort and found that late-deadline submissions were associated with lower marks, though their study did not separate submissions by task complexity. Arnold and Pistilli highlighted an important caution: system-generated data must be carefully curated before reliable conclusions can be drawn (Arnold & Pistilli, 2012).

Van Rooyen et al. (2021) found that frequent milestone submissions in continuous assessment structures reduced last-minute completion behavior at South African universities of technology, though that study did not disaggregate timing effects by submission stage or task complexity.

Together, the literature establishes that submission timing is a theoretically grounded and measurable behavioral variable, that its negative association with performance is strongest under conditions of high task complexity, and that its expression as a stable individual habit versus a situational response to difficult assessments remain poorly understood. This study addresses that gap by analyzing submission timing data across three consecutive engineering design cohorts, with specific attention to whether the effect differs between assessment stages. The methodology used to pursue this aim is described in the following section.

STUDY CONTEXT

The gap identified in the literature, specifically the absence of assessment-stage-disaggregated analyses in engineering education, is addressed within the context of a continuously assessed design module at a South African university of technology.

The Central University of Technology, Free State (CUT) is located in Bloemfontein, South Africa. Its engineering programs are accredited by ECSA and delivered within an outcomes-based framework aligned with national and international professional engineering standards. The Diploma in Engineering Technology: Electrical Engineering is a 280-credit qualification at Level 6 of the South African National Qualifications Framework (NQF), broadly comparable to a bachelor's degree, and is offered by the Department of Electrical, Electronic and Computer Engineering.

The module under investigation is Design Project III (EDP226B/A), a 14-credit NQF Level 6 module presented in the final semester of the Diploma. The module runs over a full semester, with two theory periods and five practical periods of 40 minutes each per week. Students design and build an original Arduino-based electronics project, adding at least 50% of their own design to an existing base project. Minimum required components include an Arduino microprocessor, at least two sensors, a liquid crystal display, a servo motor, and a relay module. This specification ensures a consistent level of technical complexity across cohorts.

Assessment comprises three progressive submissions. Submission 1 is a formative (in-progress) assessment that requires a project proposal and a block diagram and contributes 10% to the final mark. Submission 2 is a second formative assessment that requires a working breadboard prototype, a full schematic, a printed circuit board design, and a flowchart, and it contributes 30%. Submission 3 is the summative assessment, requiring a completed, soldered, and enclosed final project; a portfolio of evidence; a video presentation; and a live demonstration, and it contributes 60%. This weighting reflects both the complexity of the work at each stage and its position in the semester: Submission 1 carries the lowest weighting because it is an early-stage proposal, Submission 2 carries a moderate weighting because it requires a substantially greater volume of technical work, and Submission 3 is weighted at 60% both because it represents the largest component of the final portfolio and because ECSA requires that at least 60% of the module mark be moderated by an external moderator. A 10% late penalty applies to any submission within 48 hours of the deadline; work submitted beyond that window is not accepted. Among the ECSA graduate attributes formally assessed in this module, Graduate Attribute 10 (Engineering Professionalism) is specifically linked to on-time, professional submission. All submissions are managed through the Blackboard Learning Management System, which records the exact upload timestamp to the second. The methodology used to analyze this context is described in the following section.

METHODOLOGY

Building on the assessment structure described in the study context, the methodology was designed to determine whether submission hour on deadline day is a significant predictor of Submission 2 marks and final module outcomes, and whether this effect holds consistently across the three assessment stages.

An empirical, quantitative, observational research design was adopted. This approach was appropriate because the study relied entirely on archival behavioral data (timestamps and marks) generated through normal academic processes, with no researcher manipulation of conditions. The study is cross-sectional within each cohort year and longitudinal across the three-year pooled dataset.

Data Source and Collection

The dataset included all EDP226 (Design Project III) student-year records for 2023, 2024, and 2025 where complete data existed for all three submissions. Submission timestamps, accurate to the second, were extracted from the Blackboard Learning Management System (the institution-wide learning management system used at the Central University of Technology to deliver course content and manage assessment submissions) using a Python script. Each record contained the student number, the exact submission timestamp, and the mark for each submission. The late submission penalty of 10% was already embedded in all recorded marks; no further adjustment was made. The final module mark was calculated as: Final Mark = (Sub1 × 0.10) + (Sub2 × 0.30) + (Sub3× 0.60). The total sample comprised 387 student-year records: 2023 (n = 135), 2024 (n = 109), and 2025 (n = 143), as shown in Table 1.

Table 1. Participant Demographics and Submission Mark Descriptive Statistics

Academic Year	n	Sub1 Mean (%)	Sub1 SD	Sub2 Mean (%)	Sub2 SD	Sub3 Mean (%)	Sub3 SD	Final Mean (%)
2023	135	65.01	9.40	59.37	13.54	60.99	7.65	60.90
2024	109	70.47	12.19	61.37	14.43	66.00	9.33	65.06
2025	143	73.16	11.61	59.16	17.07	63.95	8.37	63.44
Pooled 2023–2025	387	69.56	11.58	59.86	15.17	63.50	8.63	63.01

Pre-Processing

Four pre-processing steps were applied before analysis:

- Timestamps were converted from ISO 8601 format to decimal hour values (e.g., 15:30:00 = 15.50) to allow continuous correlation analysis.
- For Submission 2 timing analyses, only deadline-day records were retained. In 2024, Blackboard was configured with a multi-day submission window (20–25 September), resulting in a smaller deadline-

day sub-sample (n = 64) compared with 2023 and 2025. Only students who submitted on the deadline day (25 September 2024) were included in timing analyses. This limitation is acknowledged and addressed transparently in the Results.

- Submissions received after 17:00 on deadline day were classified as Late and excluded from the primary per-band comparisons to avoid conflating submission-time-of-day effects with the late penalty effect. They were retained for the final mark trend analysis. In addition, the 26 submissions from 2024 that were recorded as submitted on earlier days of the multi-day window (rather than on the deadline day itself) were excluded from deadline-day timing analyses, as their submission hour cannot be interpreted in relation to a single closing time. This produced the final deadline-day on-time analysis sample of n = 326 (Morning n = 81, Midday n = 126, Afternoon n = 79, Last Hour n = 40).
- Student numbers were retained internally for cross-submission consistency analyses but are presented only as anonymized identifiers in all outputs.

Time Band Classification

Deadline-day submissions were assigned to one of four time bands: Morning (before 12:00), Midday (12:00–14:59), Afternoon (15:00–15:59), and Last Hour (16:00–17:00). These bands reflect natural divisions in a standard academic working day and allow detection of a distinct last-hour effect separate from general afternoon deferral.

Statistical Analysis

All analyses were conducted in Microsoft Excel using the Data Analysis ToolPak. Pearson product-moment correlations were computed between submission hour and marks, with Spearman rank-order correlations used as a non-parametric check. One-way analysis of variance tested for overall between-band differences. Independent-samples t-tests provided pairwise comparisons between the Morning band and each subsequent band. Spearman correlations across the three submissions assessed the consistency of individual submission timing behavior. An alpha level of .05 was adopted throughout, and Cohen's d is reported for key pairwise comparisons.

Assumptions and Limitations

The study assumes that Blackboard timestamps accurately reflect the moment of submission. The observational design means that causal claims cannot be made: lower marks may cause late submission (students who are underprepared may delay) rather than the reverse. The small last-hour sub-sample at Submission 1 (n = 7) limits the reliability of that specific comparison. The 2024 multi-day window produces a smaller deadline-day sample for that cohort. The study is restricted to one discipline at one institution, which limits the extent to which the findings can be generalized. These limitations are discussed further in the Discussion section. The results of applying this methodology are presented in the following section.

RESULTS

Correlation analysis, one-way analysis of variance, and independent-samples t-tests applied to the EDP226 Blackboard timestamp dataset produced the following findings, presented in line with the study aim.

Submission Timing and Submission 2 Mark

A significant negative correlation was found between Submission 2 submission hour and Submission 2 mark in the pooled deadline-day sample ($n = 326$). Pearson $r = -0.21$ ($p < .001$) and Spearman rho $= -0.24$ ($p < .001$) were closely consistent, indicating the result was not driven by distributional irregularities.

Figure 1 shows the mean Submission 2 mark by time band, with standard error bars. Table 2 provides full descriptive statistics and pairwise comparisons. Morning submitters ($n = 81$) achieved a mean of 64.22% ($SD = 13.92$). The Midday band ($n = 126$, $M = 62.00\%$) did not differ significantly from Morning ($p = .277$). The Afternoon band ($n = 79$, $M = 57.45\%$) was significantly lower ($t = 3.03$, $p = .003$, $d = 0.47$). The Last Hour band ($n = 40$, $M = 54.32\%$) showed the largest gap from Morning: 9.9 percentage points ($t = 3.54$, $p < .001$, $d = 0.69$). The overall one-way analysis of variance was significant: $F(3, 322) = 5.86$, $p < .001$.

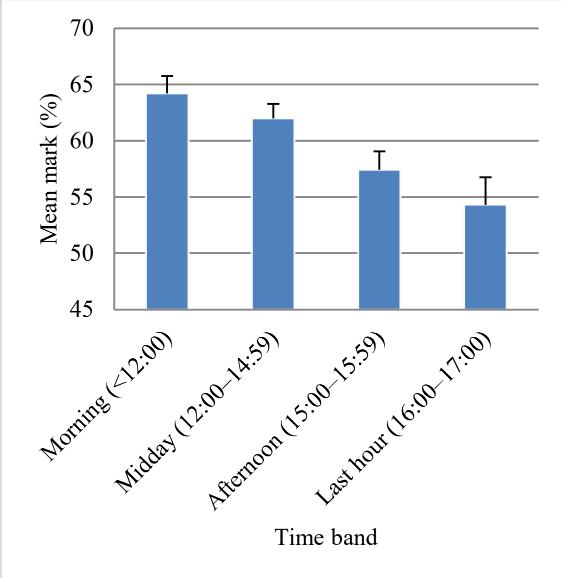

Figure 1. Mean Sub2 Mark by Time Band (Pooled 2023–2025) — bar chart with standard error bars. Morning: 64.22%; Midday: 62.00%; Afternoon: 57.45%; Last Hour: 54.32%. ** $p < .01$, *** $p < .001$ versus Morning band.

Table 2. Sub2 Mean Mark by Time Band (Pooled 2023–2025, Deadline-Day On-Time Submissions, n = 326)

Time Band	n	Mean (%)	SD	vs Morning Δ	t statistic	p value	Sig.
Morning (<12:00)	81	64.22	13.92	—	—	Reference	
Midday (12:00–14:59)	126	62.00	14.49	2.22	1.09	.277	ns
Afternoon (15:00–15:59)	79	57.45	14.33	6.77	3.03	.003	**
Last hour (16:00–17:00)	40	54.32	15.50	9.90	3.54	< .001	***

Note. Analysis of variance: F(3, 322) = 5.86, p < .001.
*** p < .01, *** p < .001 vs Morning. ns = not significant. SD = standard deviation.*

Submission Timing and Final Module Mark

Submission 2 submission hour also showed a significant negative correlation with the weighted final module mark for the full sample (n = 387): Pearson r = −0.15, p = .003. Figure 2 illustrates the step-wise decline in mean final mark from the Morning band to the Late band. Table 3 reports the full statistics.

Morning submitters achieved a mean final mark of 65.32% (SD = 8.15, n = 94). Last Hour submitters averaged 60.82% (SD = 7.86, n = 42), a difference of 4.5 percentage points (t = 3.00, p = .003, d = 0.56). Late submitters averaged 60.01% (SD = 9.86, n = 41), a difference of 5.3 points from Morning (t = 3.26, p = .001, d = 0.60).

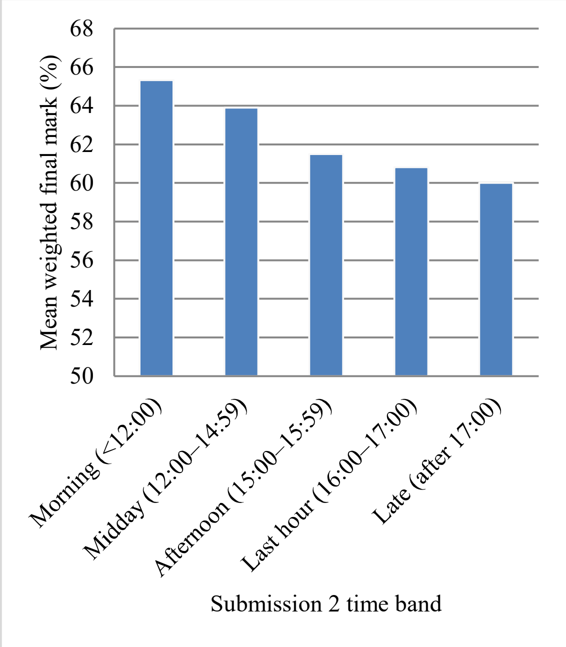

Figure 2. Weighted Final Module Mark by Sub2 Time Band (2023–2025) bar chart showing decline from Morning (65.32%) through Midday (63.90%), Afternoon (61.50%), Last Hour (60.82%) to Late (60.01%).

Table 3. Weighted Final Module Mark by Sub2 Time Band (All Students, n = 387)

Sub2 Time Band	n	Final Mean (%)	SD	SE	vs Morning Δ	t	p value
Morning (<12:00)	94	65.32	8.15	0.84	—	—	Reference
Midday (12:00–14:59)	131	63.90	8.31	0.73	1.42	—	—
Afternoon (15:00–15:59)	79	61.50	8.25	0.93	3.82	—	—
Last hour (16:00–17:00)	42	60.82	7.86	1.21	4.50	3.00	.003**
Late (after 17:00)	41	60.01	9.86	1.54	5.31	3.26	.001**

Note. Final mark = Sub1 × 0.10 + Sub2 × 0.30 + Sub3 × 0.60. Late = submission after

*17:00 on deadline day. ** p < .01.*

Specificity of the Effect Across Assessment Stages

The timing effect was not consistent across all three submissions. Table 4 shows the Morning versus Last Hour comparison at each stage. At Submission 1, a significant difference was observed between Morning (M = 70.73%) and Last Hour (M = 62.29%) submitters (t = 2.00, p = .048). However, the Last Hour group at Submission 1 comprised only n = 7 students, which makes this result unreliable. A type I error cannot be ruled out, and the finding should not be over-interpreted.

At Submission 2, the Morning versus Last Hour contrast was the strongest across all three submissions (t = 3.54, p < .001, d = 0.69), consistent with the correlation findings above. At Submission 3, there was no significant difference between Morning (M = 64.96%, n = 47) and Last Hour (M = 65.78%, n = 76) submitters (t = −0.50, p = .619). The timing effect was entirely absent at the summative stage.

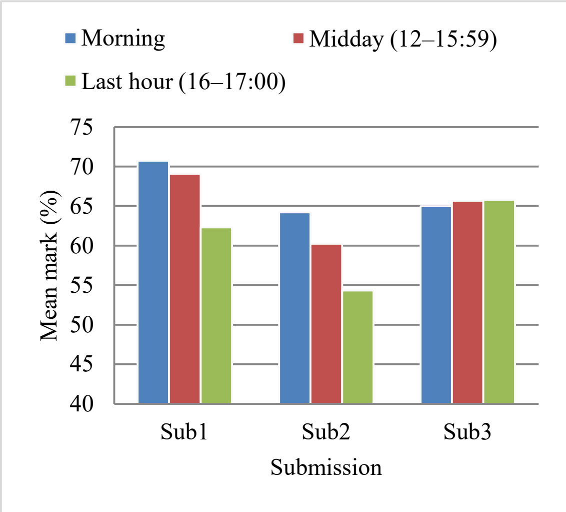

Figure 3. Morning vs Last-Hour Comparison Across All Three Submissions — grouped bar chart. Sub1: 70.73 vs 62.29 (p = .048†, n = 7 last-hour); Sub2: 64.22 vs 54.32 (p < .001***); Sub3: 64.96 vs 65.78 (p = .619, ns).

Table 4. Morning vs Last-Hour Mark Comparison Across All Three Submissions (Pooled 2023–2025)

Submission	Morning n	Morning Mean (%)	Last-Hour n	Last-Hour Mean (%)	Δ	t	p value
Sub1 (10%)	127	70.73	7	62.29	8.45	2.00	.048†
Sub2 (30%)	81	64.22	40	54.32	9.90	3.54	< .001***
Sub3 (60%)	47	64.96	76	65.78	−0.83	−0.50	.619 ns

Note. † Sub1 last-hour n = 7; interpret with caution.
**** p < .001. ns = not significant.*

Consistency of Submission Timing Within Students

To assess whether late-hour submission was a stable habit or a situational response, Spearman rank-order correlations were computed between each student's submission hours across the three assessments. The Submission 1-to-Submission 2 correlation was rho = .38 (p < .001), Submission 2-to-Submission 3 was rho = .43 (p < .001), and Submission 1-to-Submission 3 was rho = .32 (p = .001). These moderate correlations indicated some within-student consistency across the semester.

However, 68% of students submitted Submission 2 later in the day than they had submitted Submission 1, indicating a consistent directional shift toward later submission at the more technically demanding stage. More importantly, most students classified as Last Hour submitters at Submission 2 had submitted in the Morning or Midday band at Submission 1. This indicated that submitting in the last hour at Submission 2 was largely a situational response to the increased technical demands of that assessment, rather than a habitual pattern. Figure 4 shows the per-year breakdown of Submission 2 mean marks by time band, confirming the direction of the effect in 2023 and 2025, while the attenuated pattern in 2024 reflects the smaller sample on deadline day for that cohort. The considerable spread of marks within each time band across all three cohort years confirms that submission timing was one factor among several influencing performance.

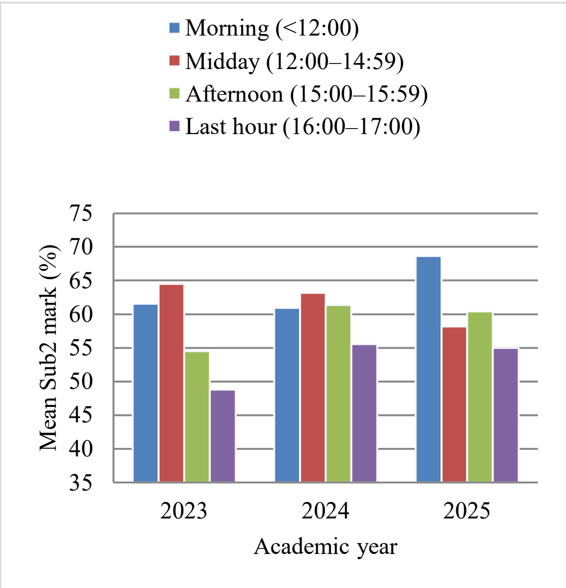

Figure 4. Sub2 Timing Effect Per Academic Year (2023–2025)

These findings are interpreted and discussed in the following section.

DISCUSSION

The main finding of this study is that the hour of submission at Submission 2, which is the most technically demanding formative assessment in EDP226, predicted both the Submission 2 score and the final module grade. In contrast, no similar effect was observed at Submission 3. This directly fulfills the study's objective and offers valuable insights into how timing behavior influences performance in engineering design modules.

The negative correlation between Submission 2 submission hour and Submission 2 mark ($r = -0.21$, $p < .001$) and the 9.9 percentage point gap between Morning and Last Hour submitters fall within the range reported in the broader procrastination literature. Steel's (2007) meta-analysis found correlations between procrastination and performance of −0.19 to −0.28, and the current finding sits squarely within that range (Steel, 2007). Lotz et al. (2022) reported a similar pattern in an engineering assignment context. What the present study adds is the demonstration that this effect is task-specific: it is clearly present at Submission 2, which demands a working prototype, schematic, and printed circuit board design, but entirely absent at Submission 3. This pattern is consistent with Klassen et al.'s finding that late submission under pressure reflects not just poor time management, but inadequate technical preparation, as students who had not yet resolved their design problems were still working at the last hour (Klassen et al., 2008).

The absence of the timing effect at Submission 3 requires explanation. Two factors are likely at play. First, Submission 3 is an exhibition-style assessment: the final project must physically work, be properly constructed, and be presented on video. These requirements are difficult to complete at the last minute, unlike a documentation submission; the quality of the physical artifact is largely determined by weeks of prior work, regardless of when the submission is uploaded. Broadbent and Poon found that sustained project-completion tasks were less sensitive to last-minute self-regulatory failures than documentation-based assessments, which aligns with this interpretation (Broadbent & Poon, 2015). Second, the Last Hour group at Submission 3 was substantially larger (n = 76) than at Submission 2 (n = 40), and included many students who were not last-hour submitters at Submission 2. This dilution of the group composition is consistent with Arizmendi et al.'s (2023) observation that submission timing behavior is context-dependent and sensitive to the specific demands of each assessment stage rather than a fixed individual trait (Arizmendi et al., 2023).

The carry-through of the Submission 2 timing effect to the final mark ($r = -0.15$, $p = .003$) is modest in size but practically meaningful. A 4.5 percentage point gap in final mark between Morning and Last Hour Submission 2 submitters represents a real difference in academic outcome, especially for students whose cumulative average determines their standing in the program. Van Rooyen et al. (2021) reported similar downstream effects of formative submission behavior on summative outcomes in South African university of technology contexts. From a learning analytics perspective, this finding supports the use of Submission 2 submission timing as an early warning signal, one that is available at the mid-semester point, well before the 60%-weighted final submission (Arnold & Pistilli, 2012; Herodotou et al., 2020).

The cross-submission timing correlations (rho = .32 to .43) indicate moderate consistency within individuals. Yet the majority of Last Hour Submission 2 submitters had not been last-hour submitters at Submission 1, confirming that the behavior was largely situational. Students appear to have encountered the increased complexity of Submission 2, which required integrated hardware and software design rather than just a proposal, and deferred completion in a way that reflected task-specific difficulty rather than habitual procrastination. This nuances the self-regulated learning framework of Zimmerman and Pintrich: general SRL capacity sets the background conditions, but individual assessments can trigger situational failures when task difficulty increases beyond a student's prior experience (Pintrich, 2004; Zimmerman, 2000).

Limitations

Several limitations must be kept in mind. The observational design prevents causal inference: underprepared students may submit late because they are underprepared, rather than performing poorly because they submitted late. The 2024 multi-day Blackboard window substantially reduced the deadline-day sample for that cohort and weakened the per-year replication, as seen in the non-significant 2024 result (p = .442). The Sub1 last-hour comparison group (n = 7) is too small for confident conclusions. The study covers a single discipline at a single institution, and its findings may not transfer to other engineering contexts without replication. Individual student characteristics such as prior academic performance, language of instruction, or socioeconomic background were not controlled for, and these may confound the relationship between timing and marks. These findings have several implications that are summarized in the conclusion that follows.

CONCLUSION

This study aimed to determine whether the hour at which a student submits the most technically demanding formative assessment in an engineering design module predicts both that assignment mark and the final module outcome, and whether any such effect is specific to that assessment stage.

The findings confirm that it does and that it is. Students who submitted Submission 2 in the last hour before the deadline scored 9.9 percentage points lower than Morning submitters on that assessment, and 4.5 percentage points lower on the final module mark. This effect was absent at the summative final submission, where Morning and Last-Hour submitters performed identically (p = .619). Within-student analysis showed that last-hour submissions at Submission 2 were predominantly situational responses to the increased technical demands of that stage, rather than a fixed individual habit.

The practical significance of these findings is that Submission 2 submission timing is a low-cost, passively collected indicator available at the mid-semester point, before the 60%-weighted summative submission. Identifying students who submit in the Afternoon or Last Hour band at Submission 2 provides an actionable basis for early academic support, consistent with both the learning analytics literature and the engineering professionalism requirements of ECSA Graduate Attribute 10.

The study's limitations include the observational design, the reduced sample on deadline day in 2024, the small Sub1 last-hour comparison group, the single-institution scope, and the absence of individual covariate controls.

Four recommendations follow from these findings. First, learning management systems should be configured with a single specific deadline time for each assessment, rather than a multi-day window, to ensure that deadline-day timing analyses remain valid and comparable across cohorts. Second, module coordinators should use the Submission 2 submission band (Morning/Midday versus Afternoon/Last Hour) as a trigger for proactive academic support contact at mid-semester, before the final submission. Third, this study should be replicated in other engineering design modules at other institutions, with individual-level covariates included to isolate the independent contribution of submission timing. Fourth, the approach developed here (classifying deadline-day submission hours into interpretable bands and correlating them with marks) could be readily incorporated into institutional learning analytics dashboards as a practical early-warning tool. In future studies, students will also be interviewed, so that the reasons behind early or late submission behavior can be identified directly.

Author Contributions

Conceptualization, Methodology, Software, Formal Analysis, Investigation, Data Curation, Writing Original Draft, Writing Review & Editing, Visualization, Project Administration.

Ethical Clearance

This study used anonymized archival submission timestamp and grade data generated through normal academic processes at the Central University of Technology, Free State. No human participants were recruited, no interventions were administered, and no personal identifying information was collected or processed. Formal ethics committee approval was not required under institutional policy for the analysis of de-identified administrative records. All student data were handled in accordance with the Protection of Personal Information Act (POPIA) of South Africa.

Conflict of Interest

The author declares no conflict of interest.

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