Overburdened by Debt: A Quantitative Study of Process Debt's Effect on Workload in Agile Teams

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Abstract

Building upon the analogy of Technical Debt, Process Debt refers to issues arising from inefficient or obsolete processes, which can substantially restrict an organization's effectiveness in delivering software. Process Debt creates additional tasks, such as rework, clarification, and workaround efforts, which can significantly increase the workload experienced by developers. A heightened workload may lead to stress and burnout. This study empirically examines the quantitative impact of five types of Process Debt on workload among Agile Software Development teams. Survey data from 191 participants in two large organizations revealed significant correlations between all Process Debt types and increased workload. Multiple regression analysis further identified Synchronization Debt, Roles Debt, and Infrastructure Debt as key predictors, highlighting their critical roles in intensifying workload pressures. These findings underscore the importance of proactively addressing specific areas of Process Debt, enabling organizations to enhance process efficiency, reduce developer overload, and maintain sustainable productivity.

Keywords: Process Debt, Technical Debt, Agile Software Development, Workload.

1. Introduction

Process Debt (PD) has become an increasingly recognized challenge within Agile Software Development (ASD) contexts, characterized by inefficiencies and inadequacies in work processes that introduce additional burdens on development teams [20, 21]. While significant attention has traditionally focused on Technical Debt (TD), particularly its implications for software maintainability and system architecture [16], the role of PD in shaping team workflows and organizational productivity has become a topic of recent academic focus [1], [9], [19]. Alves et al. [2] expanded the scope of the debt metaphor, categorizing PD as one of several debt types, emphasizing its distinct impact on procedural rather than technical aspects of software development.

Process inefficiencies arising from PD, such as unclear roles and responsibilities, unsynchronized activities, unsuitable documentation, and outdated infrastructure, can significantly disrupt workflow, creating additional, often unnecessary workload for developers [6], [20]. These inefficiencies compel team members to spend extra time clarifying tasks, managing redundant work, and correcting errors resulting from ambiguous or inadequate processes [23]. Martini et al. [20] highlight that PD initially manifests as operational overhead, mistakes, and increased frustration, leading to increased workload, affecting individual productivity and overall organizational efficiency over time.

Workload is a critical factor influencing developers' productivity and general well-being [22]. Extensive research links excessive workload to increased stress, burnout, and diminished productivity [22], [28], [31]. An excessive workload not only reduces developers' immediate efficiency but also negatively impacts their capacity for innovation and quality assurance, potentially leading to a decline in software quality [4], [11].

This misalignment is especially problematic in ASD environments, where flexibility, rapid iteration, and team autonomy are essential [26]. When outdated, waterfall-like processes constrain teams, they face increased overhead, coordination challenges, and delays undermining the core principles of agility [26]. Therefore, studying PD in this context is critical, as even small inefficiencies can accumulate rapidly and obstruct the responsiveness and adaptability that agile methods are designed to support.

Despite the recognized importance of managing workload to sustain developer productivity and organizational health, empirical research specifically quantifying the impact of PD on workload remains sparse. Most existing studies addressing PD have been qualitative, highlighting experiences and perceptions of inefficiencies without quantitatively measuring their impact on workload [1], [20], [23]. Thus, there is a clear need for systematic empirical studies that quantify how different types of PD directly increase workload within software development teams.

Therefore, this research aims to bridge this gap by empirically investigating how different types of PD, namely Process Unsuitability, Roles Debt, Synchronization Debt, Documentation Debt, and Infrastructure Debt, quantitatively affect the perceived workload of software developers. This study investigates survey data collected from agile teams, building on the framework provided by Martini et al. [20] and previously applied to understand other impacts of PD [14]. This study, therefore, builds on the earlier study by Gustavsson et al. [14] where the risk of decreased job satisfaction was investigated quantitatively. By focusing specifically on workload, this research aims to provide actionable insights to guide targeted interventions, enabling organizations to manage better and mitigate the workload-related consequences of process inefficiencies in ASD contexts.

The remainder of this paper is structured as follows: Section 2 provides a background, further contextualizing PD and workload within ASD environments. Section 3 outlines the research methodology, including the operationalization of workload and PD types, the formulation of hypotheses, and data collection approaches. Section 4 presents the data analysis and findings. Section 5 discusses these findings in relation to the broader theoretical and practical implications for managing PD, identifies limitations, and suggests avenues for future research. Finally, Section 6 summarizes the conclusions.

2. Process Debt

PD represents inefficiencies embedded within organizational procedures, identified explicitly as suboptimal practices that, although initially implemented for short-term gains or convenience, subsequently cause increased effort and challenges in software development activities [21]. Beyond the well-established concept of TD, which primarily addresses code and architectural trade-offs, PD encompasses procedural inadequacies that result in workflow disturbances, operational confusion, and ultimately additional workload [6], [20].

Martini et al. [20] categorize PD into five primary types relevant to ASD contexts: Process Unsuitability, Roles Debt, Synchronization Debt, Documentation Debt, and Infrastructure Debt. Each of these types uniquely contributes to workload increases within agile teams. For instance, Process Unsuitability arises when organizational procedures fail to align with the team's practical needs, often forcing developers to spend excessive time on unnecessary or poorly tailored process steps, thereby directly increasing their workload [4], [23], [29].

Roles Debt, characterized by unclear or conflicting role definitions, significantly complicates task assignment and accountability, resulting in duplicated efforts and heightened uncertainty, intensifying individual workloads [17], [20], [24]. Similarly, Synchronization Debt arises when parallel processes lack sufficient coordination, often resulting in repeated rework, missed steps, and productivity disruptions, each incrementally contributing to the workload burden of development teams [12], [30]. Documentation Debt refers to insufficient, outdated, or overly complex documentation, which requires developers to expend additional cognitive and temporal resources to decipher process requirements or clarify task execution procedures, thereby further contributing to workload intensity [18, 19]. Finally, Infrastructure Debt, containing outdated, insufficiently integrated, or unsuitable technological tools and platforms, forces team members into supplementary manual activities or cumbersome workarounds, thereby inflating workload demands [23, 24].

Research has repeatedly underscored the critical importance of managing workload to ensure sustainable productivity, prevent burnout, and maintain high software quality standards [22], [28], [36]. The negative impacts of excessive workload are profound, affecting not only immediate productivity but also long-term psychological well-being, innovation capability, and retention rates among software developers [33], [36]. Thus, investigating the linkage between PD and perceived developer workload becomes imperative from both theoretical and practical perspectives.

Despite these insights, empirical quantification of how specifically defined PD types affect developer workload within ASD teams remains limited. Qualitative studies have provided foundational understanding by highlighting perceived impacts, but rigorous quantitative assessments are necessary to verify these findings [1], [19, 20, 21].

This study addresses this gap by empirically examining how each PD type contributes distinctively to developer workload in ASD teams. It provides insights into understanding and mitigating these effects, which are crucial for organizational leaders seeking to refine agile practices, optimize team workflows, and effectively manage software developer workloads.

3. Method

This study adopts a quantitative approach, employing a survey-based methodology to investigate the relationship between PD types and perceived self-reported workload within ASD teams. The survey instrument was systematically developed and validated to ensure a robust measurement of the relevant constructs, building on established frameworks and adapting them to specifically address the impacts of software developer workload in ASD contexts. Martini et al. [20] were chosen as the reference for categorizing PD types due to their comprehensive and clearly articulated classification. Their categorization is grounded in empirical exploration and extensive qualitative research, making it robust for investigating PD-related challenges.

3.1. Operationalization of Constructs

Workload was operationalized using a survey scale comprising six items previously employed by Gray-Stanley and Muramatsu [10] based on earlier work by Caplan [5]. Items were formulated to capture both quantitative workload (the sheer volume of tasks) and qualitative workload (complexity and cognitive demands of tasks). In the study by Gray-Stanley and Muramatsu [10], the scale demonstrated a Cronbach's α value of 0.83. This study's value was 0.84 (see Table 1 below). The response scale used a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

PD types (i.e., Process Unsuitability, Roles Debt, Synchronization Debt, Documentation Debt, and Infrastructure Debt) were operationalized using survey items refined through rigorous pre-testing and validation stages involving subject matter experts and pilot studies within ASD teams. The pilot field study of the survey instrument was presented at a conference in 2024 [13], and the survey scales were further improved through a second field study within two large software development organizations [14]. The survey instrument used to measure PD in this study is presented in Gustavsson et al. [14] and the instrument used to measure perceived self-reported workload is presented in the paper by Gray-Stanley and Muramatsu [10].

Items measured the extent to which team members perceived the five different PD types, also employing a 7-point Likert scale. The scales had Cronbach's αs ranging from 0.74 (acceptable) to 0.82 (good). The Cronbach αs measured for Documentation Debt (0.82), Infrastructure Debt (0.81), and Sync Debt (0.8) were good. Process Unsuitability Debt (0.75) and Roles Debt (0.74) were acceptable. According to Streiner [32], a Cronbach's α of less than 0.5 is unacceptable, between 0.5 and 0.6 is poor, and between 0.6 and 0.7 is questionable. As presented, none of the scales had Cronbach's αs below 0.7.

3.2. Hypotheses Development

Given the current uncertainty regarding the relationship between the dependent and independent variables, we initially conducted a bivariate correlation analysis. Consequently, we formulated our research hypothesis, declaring that each of the five identified PD types would correlate with workload, as measured according to Gray-Stanley and Muramatsu [10].

The null hypothesis (H0) for all tests states that the correlation coefficient is zero, indicating no significant relationship between workload and the PD types under consideration. The five alternative hypotheses are detailed as follows:

H1: There is a significant correlation between increased perceived workload and Process Unsuitability.

H2: There is a significant correlation between increased perceived workload and Roles Debt.

H3: There is a significant correlation between increased perceived workload and Synchronization Debt.

H4: There is a significant correlation between increased perceived workload and Documentation Debt.

H5: There is a significant correlation between increased perceived workload and Infrastructure Debt.

3.3. Data Collection Procedure

Data was collected from two large software development organizations in Sweden. The organizations were found through our research network. Each potential respondent received a unique survey link via a secure email distribution list, ensuring that no individual could submit multiple responses. The participants involved diverse roles within ASD teams, including developers, testers, designers, and scrum masters, to ensure comprehensive insights into how PD impacts perceived self-reported workload. The first organization, Company 1, is a consultancy firm operating within the telecommunications sector, where the studied department is tasked with developing and enhancing a software product that has continuously improved over the past two decades. Company 1 introduced ASD values and principles in 2009 and currently employs a large-scale agile framework to coordinate the activities of its fourteen teams.

Company 2 operates in the financial technology (Fintech) sector, explicitly developing systems for the insurance industry. The department studied in this organization focuses on integrating multiple internal systems. Agile values and principles were adopted by Company 2 in 2010, utilizing similar large-scale agile practices employed by Company 1, including multi-team planning sessions, cross-team coordination meetings, and multi-team reviews. The data collection took place between November 2023 and January 2024, utilizing an online survey platform provided by our university.

Survey invitations were distributed during departmental planning sessions to enhance response rates and ensure data reliability, and managers encouraged participants to complete them immediately. Respondents received assurances of anonymity and confidentiality, and no personally identifiable information was collected. A total of 191 usable responses were obtained, resulting in an overall response rate of approximately 65% within these departments. Additionally, to encourage participation, we provided insights into the results and sent a follow-up reminder two weeks after the initial contact. We believe that this contributed to the high response rate.

Participants' professional experience was broadly distributed: 14.1% had over 30 years of experience, 26.2% had more than 20 years, 20.4% had more than 10 years, and 39.2% had fewer than 10 years. To capture personal experiences comprehensively, this study did not differentiate between participants based on team type or specific organizational roles. Additionally, the exact organizational placement of participants and the precise nature of their development tasks were not examined. Nevertheless, collecting data from two distinct companies enhances the study's external validity.

3.4. Data Analysis

Statistical analyses involved descriptive statistics to understand data distribution and correlation analyses to examine initial relationships between variables. Subsequently, multiple regression analysis was employed to test the formulated hypotheses, determining the strength and significance of the relationship between each PD type and perceived self-reported workload.

The methodological rigor and the comprehensive approach to survey instrument development and validation provided a reliable basis for analyzing the complex relationships between PD and developer workload.

4. Results

This section presents the findings of the statistical analyses performed to evaluate the relationships between different types of PD and workload within ASD teams.

4.1. Descriptive Statistics

Table 1 summarizes the descriptive statistics for perceived self-reported workload and PD types collected by survey respondents. Several statistical analyses were performed to assess the normality of the data distribution. These included the examination of Q-Q plots, skewness and kurtosis tests, and the Shapiro-Wilk test. Typically, skewness values between -2 and +2 and kurtosis values between -4 and +4 are considered indicative of acceptable normality [35]. As shown in Table 1, all variables fell within these acceptable ranges.

Additionally, the Shapiro-Wilk test, frequently regarded as the most robust method for testing normality due to its superior power in detecting non-normal distributions, was conducted. With a significance threshold of 0.01 [34], the Shapiro-Wilk test results indicated that all variables met the criteria for normal distribution except the Workload construct. The p-values obtained were as follows: Workload ($p = 0.003$), Process Unsuitability ($p = 0.212$), Roles Debt ($p = 0.016$), Synchronization Debt ($p = 0.098$), Documentation Debt ($p = 0.109$), and Infrastructure Debt ($p = 0.017$). Although the Workload construct did not pass the Shapiro-Wilk test, the skewness and kurtosis values are well within the boundaries of normality which supports our decision on using parametric tests for analysis.

Table 1. Descriptive statistics.

Variable	Mean	SD	Cronbach's α	Skewness	Kurtosis	Shapiro-Wilks p-value
Workload	4.52	1.20	0.84	-0.40	-0.45	0.003
Process Unsuitability	4.70	1.02	0.75	-0.25	0.05	0.212
Roles Debt	4.91	1.03	0.74	-0.42	0.44	0.016
Sync Debt	4.23	1.22	0.8	0.09	-0.39	0.098
Documentation Debt	4.24	1.08	0.82	-0.14	-0.24	0.109
Infrastructure Debt	4.48	1.16	0.81	-0.44	0.14	0.017

4.2. Correlation Analysis

We conducted bivariate correlation analyses using the average scores from each PD type and workload to explore the relationships between the various PD types and workload.

Pearson's product-moment correlation coefficient was employed to quantify the correlations between the dependent and independent variables (see Table 2).

Table 2. Pearson correlations of variables (N=191).

	1. W	2. PU	3. RD	4. SD	5. DD	6. ID
1. Workload (W)	1					
2. Process Unsuitability (PU)	0.423***	1				
3. Roles Debt (RD)	0.493***	0.565***	1			
4. Sync Debt (SD)	0.518***	0.604***	0.590***	1		
5. Documentation Debt (DD)	0.329***	0.568***	0.455***	0.506***	1	
6. Infrastructure Debt (ID)	0.397***	0.562***	0.345***	0.433***	0.496***	1

* $p < .05$, ** $p < .01$, *** $p < .001$

Due to uncertainty regarding the directionality of these correlations, we utilized two-tailed tests. We assessed the effect sizes by referencing the guidelines provided by Cohen [7]. According to Cohen's recommendations, an effect size is considered small if the correlation coefficient is approximately 0.10, medium if it is around 0.30, and large if it is close to 0.50. A large effect size implies a strong likelihood of observing similar associations in related research, whereas a medium effect size suggests a moderate likelihood of replication in other studies [7]. To minimize the risk of false positives, we set the significance level (α) at 0.05 and defined medium as our threshold for practical significance.

As presented in Table 2, Synchronization Debt and Roles Debt exhibited a large effect size (close to 0.5) and a statistically significant relationship with workload. Process Unsuitability, Documentation Debt, and Infrastructure Debt demonstrated medium effect sizes (all above 0.3) and statistically significant correlations with workload. Consequently, we rejected the null hypothesis in favor of hypotheses H1, H2, H3, H4, and H5. This outcome indicates that elevated PD levels are associated with higher perceived workload across all PD types analyzed. Nevertheless, since the analysis performed was bivariate, causality cannot be determined definitively. While theoretically possible, the alternative scenario in which increased workload causes greater PD appears unlikely, as logically reduced workload would not typically lead to diminished organizational process inefficiencies.

4.3. Multiple Regression Analysis

A confirmatory multiple regression analysis was conducted to evaluate the effectiveness of the PD variables in predicting workload, adhering to established methodological guidelines by Hair et al. [15]. A confirmatory approach implies that all independent variables under study (Process Unsuitability, Roles Debt, Synchronization Debt, Documentation Debt, and Infrastructure Debt) are simultaneously included in the regression model. To ensure the reliability and accuracy of the analysis, several critical assumptions underpinning multiple regression were examined, including linearity, independence of errors, normality, multicollinearity, and homoscedasticity.

Linearity, indicating a direct relationship between independent and dependent variables, was verified visually through scatter plots. The inspection confirmed the presence of linear relationships. The assumption of independence of errors was assessed using the Durbin-Watson test [15]. The calculated value of 1.793 fell within the acceptable range of 1.50 to 2.50, confirming no significant autocorrelation among residuals.

Multicollinearity, which occurs when independent variables exhibit excessive intercorrelations, can adversely impact regression coefficient estimates, leading to interpretational inaccuracies [25]. To assess potential multicollinearity, correlation coefficients among the independent variables were reviewed, adhering to the criterion suggested by Young [37], which indicates problematic multicollinearity when values exceed 0.8. The observed correlations (presented in Table 2) remain below this threshold. Additionally, variance inflation factors (VIFs) and tolerance levels were calculated to further test for multicollinearity. Tolerance values exceeding 0.10 and VIF values below

10, as recommended by Belsley [3], confirmed the absence of multicollinearity in this analysis, as presented in Table 4.

Table 3. Confirmatory specification and analysis of variance.

Multiple R			0.592		
Coefficient of determination (R^2)			0.350		
Adjusted R^2			0.333		
RMSE			0.982		
	Sum of Squares	df	Mean Square	F	Sig
Regression	96.257	5	19.251	19.949	< 0.001
Residual	178.534	185	0.965		
Total	274.791	190			

Table 4. Variables entered into the regression model.

	Regression coefficients			Statistical sig.		Correlations		Collinearity stat.	
	B	Std E	Beta	t	Sig.	Partial	Part	Tolerance	VIF
Process Unsuitability	0.015	0.104	0.013	0.144	0.885	0.011	0.009	0.451	2.218
Roles Debt	0.312	0.091	0.266	3.408	<0.001	0.243	0.202	0.574	1.741
Sync Debt	0.288	0.081	0.292	3.549	<0.001	0.252	0.210	0.520	1.924
Documentation Debt	-0.048	0.086	-0.043	-0.557	0.578	-0.041	-0.033	0.592	1.690
Infrastructure Debt	0.199	0.077	0.193	2.585	0.010	0.187	0.153	0.633	1.581

The outcomes of the confirmatory multiple regression analysis are summarized in Tables 3 and 4 above. The model explained approximately 33.3% of the variance in workload (Adjusted $R^2 = 0.333$), indicating substantial explanatory power. The significant difference between the mean squares for regression (19.251) and residual (0.965), alongside an F-statistic of 19.949 ($p < 0.001$), confirmed that the PD variables collectively provided significant predictive value regarding workload.

Specifically, Synchronization Debt ($B = 0.288$, $p < 0.001$), Roles Debt ($B = 0.312$, $p < 0.001$), and Infrastructure Debt ($B = 0.199$, $p = 0.010$) emerged as statistically significant predictors. Their positive coefficients suggest that higher perceptions of these debt types correlate directly with increased perceived self-reported workload. Among these predictors, Synchronization Debt displayed the strongest influence on workload ($\beta = 0.292$), followed closely by Roles Debt ($\beta = 0.266$), and Infrastructure Debt ($\beta = 0.193$). In contrast, Process Unsuitability ($B = 0.015$, $p = 0.885$) and Documentation Debt ($B = -0.048$, $p = 0.578$) did not significantly predict workload within this regression model.

5. Discussion

The results of this study offer partial empirical support for the claims made by Martini et al. [19] regarding the detrimental effects of PD on developers' working conditions. Martini et al. [19] argue that PD introduces inefficiencies into everyday workflows, contributing to increased workload, error rates, elevated cognitive load [23, 24], and reduced morale among developers. Our findings align with and refine these assertions by identifying statistically significant correlations in the multiple regression tests between specific types of PD — namely, Synchronization Debt, Roles Debt, and Infrastructure Debt — as independent variables, and perceived workload as the dependent variable. This suggests that these particular types of process inefficiencies may have significantly adverse implications for developers' work environments.

Notably, the model yielded an adjusted R^2 value of 0.333, indicating that the five PD types included in the regression accounted for approximately 33.3% of the variance in perceived increased workload. In behavioral and organizational research, where numerous variables often interact, an adjusted R^2 of this magnitude is considered meaningful. This substantial proportion of explained variance underscores the critical need to manage Synchronization Debt, Role Debt, and Infrastructure Debt to alleviate workload pressures and enhance working conditions for software development teams.

Correlation analysis demonstrated significant relationships between all investigated PD types and perceived self-reported workload, reinforcing previous qualitative assertions that process inefficiencies substantially impact developer workload [20, 21]. These results indicate that each PD type makes a distinct yet significant contribution to increasing the workload among software development professionals.

Further insights emerged from the multiple regression analysis. The identified significance of Synchronization Debt (Beta value of 0.292) emphasizes the critical importance of well-coordinated processes to prevent duplication and rework, a particularly salient issue in large-scale agile environments where team interdependencies are complex [12]. Roles Debt, with a Beta value of 0.266, highlights how ambiguity and overlap in roles directly intensify workload through repeated task clarification and responsibility reassignment, consistent with prior qualitative findings [17], [19]. Similarly, Infrastructure Debt, reflected by a Beta value of 0.193, confirms that inadequate tools and technologies notably inflate workload through additional manual labor and workaround practices, resonating with earlier qualitative observations [19, 20], [23, 24].

As previously stated, this study builds on the study by Gustavsson et al. [14] investigating how PD affects job satisfaction. Both studies are performed in the same organizations and the previous study [14] showed a significant correlation between job satisfaction and the two PD types Process Unsuitability and Roles debt. This study further proves the importance of Roles debt as it is significantly correlating both job satisfaction and workload.

Interestingly, despite their significant correlation to workload, Process Unsuitability and Documentation Debt were not significant predictors in the regression model when considered alongside other PD types. This suggests that while these types of PD impact workload individually, their effects might be less critical or potentially moderated when analyzed together with Roles Debt, Synchronization Debt, and Infrastructure Debt. This could imply that developers are somewhat more tolerant or adaptive to unsuitable processes and suboptimal documentation, possibly compensating through frequent interpersonal interactions typical of agile practices [27].

While this study was conducted within the context of ASD teams, we recognize that the underlying dynamics of PD and its impact on workload may extend beyond ASD environments. The inherent flexibility and iterative nature of ASD practices [8] may help buffer some of the adverse consequences associated with process inefficiencies. Conversely, in more plan-driven or traditionally structured development settings, where procedural rigidity and limited responsiveness to change are more common [26], the negative effects of PD might be equally pronounced or potentially even more severe.

5.1. Theoretical Implications

Although scholarly interest in PD has increased in recent years [1], [9], [19, 20, 21], a notable gap in empirical research remains, hindering the quantification of its effects and the development of effective management strategies. Existing qualitative investigations have yielded important insights into the nature of PD. Yet, there is a distinct need for quantitative approaches that can establish robust, measurable links, particularly between PD and workload. This study addresses this gap by providing empirical evidence of statistically significant relationships between various types of PD and perceived workload.

The findings validate the hypothesis that different manifestations of PD are strongly associated with increased workload among software developers. The observed correlations across all five PD types (Process Unsuitability, Roles Debt, Synchronization Debt, Documentation Debt, and Infrastructure Debt) underscore the extensive impact that procedural inefficiencies exert on developers' day-to-day efforts. These results are consistent with the theoretical model proposed by Martini et al. [20], which supports the assertion that PD contributes to increased workload and potentially influences broader aspects, such as well-being and productivity [31], [36].

5.2. Practical Implications

The results offer clear guidance for agile practitioners and organizational leaders. The identification of Roles Debt, Synchronization Debt, and Infrastructure Debt as significant predictors of workload suggests the need for prioritized management interventions in these areas. These insights suggest a clear prioritization strategy for ASD organizations: efforts should concentrate primarily on clarifying roles and responsibilities, enhancing synchronization between parallel workflows, and maintaining suitable technological infrastructures.

Organizations can benefit from explicitly addressing role definitions through structured role clarification processes, enhancing team synchronization practices, and investing strategically in practical technological tools and infrastructure. Specifically, targeted management interventions could include role clarification workshops, improved cross-team coordination practices, and strategic investments in tools and platforms designed to streamline workflows and reduce manual effort. Implementing targeted improvements in these critical areas may significantly reduce workload, enhance productivity, and improve employee satisfaction [31].

5.3. Limitations

Although this study offers meaningful insights into the relationship between PD and perceived workload, several limitations should be acknowledged. First, the use of self-reported measures for both workload and PD introduces the possibility of subjective bias [15]. Individuals' perceptions may be influenced by personal or contextual factors, which can potentially affect the reliability of the data. This concern is presented in prior research [31], which recognizes that perceptual assessments, particularly those of productivity and workload, are susceptible to individual variance.

Second, the cross-sectional design of the study constrains the ability to infer causality regarding the observed associations between PD and workload [15]. Longitudinal studies would be better positioned to explore how PD evolves over time and how its influence on workload may fluctuate across different development phases or organizational changes.

Third, the empirical context of this research was limited to two organizations operating within Sweden. Cultural and organizational characteristics specific to this setting may limit the generalizability of the findings. To enhance external validity, future research should replicate the study across a broader range of geographical and organizational contexts.

Finally, future investigations could also improve the robustness of findings by triangulating self-reported data with objective workload indicators, such as time tracking, error rates, or system usage logs, to complement subjective perceptions with measurable behavioral data.

5.4. Future research

Although we refrain from making broad generalizations without further empirical validation, our findings suggest promising avenues for future research. Given that the multiple regression analysis revealed that only certain types of PD were significant predictors of workload, future research should explore these dynamics in greater detail. Specifically, further investigation is warranted into the PD types that showed statistically significant effects, namely, Synchronization Debt, Roles Debt, and Infrastructure Debt, to develop focused interventions aimed at balancing perceived workload within ASD environments.

To extend the contributions of this study, longitudinal research is recommended to evaluate how targeted efforts to mitigate PD influence workload and productivity over time. Such studies would offer greater clarity on causal relationships and the sustained impact of PD management practices.

Considering the finding that PD accounts for 33.3% of the variance in perceived workload (Adjusted $R^2 = 0.333$), future work should also examine the influence of broader contextual and organizational variables. Factors such as company culture, leadership styles, and organizational maturity may serve as moderators in the relationship between PD and workload. Understanding these contextual elements could support the design of more nuanced and effective strategies for mitigating PD's adverse effects.

Moreover, an important direction for future research involves exploring role-based and team-level differences in the experience of PD. It is plausible that developers, testers, designers, and other stakeholders perceive and are affected by specific types of PD in distinct ways. Investigating these role-dependent perceptions may yield more refined insights into PD's impact. Subsequent studies could investigate whether the relationships observed between PD and workload in ASD contexts are similarly applicable in other organizational frameworks and software development paradigms.

Additionally, examining variability across teams could illuminate how intra-team dynamics, coordination patterns, and communication structures shape the relationship between PD and workload, informing the development of team-specific interventions.

Finally, future studies should explore the intersection of PD and TD. Given the often intertwined nature of these forms of debt, integrated research efforts could lead to more holistic and comprehensive debt management frameworks within ASD contexts.

6. Conclusion

This study aimed to empirically investigate the relationships between various types of PD and perceived workload within ASD teams. By systematically exploring five distinct types of PD (Process Unsuitability, Roles Debt, Synchronization Debt, Documentation Debt, and Infrastructure Debt), we provided quantitative evidence illustrating how specific process inefficiencies significantly impact workload perceptions among software developers.

The results underscore the critical roles that Synchronization Debt, Roles Debt, and Infrastructure Debt play in influencing perceived workload, each demonstrating statistically significant predictive power in the regression analysis. Notably, Synchronization Debt emerged as the most substantial contributor, closely followed by Roles Debt and Infrastructure Debt. This highlights the necessity for ASD teams to maintain effective synchronization across processes, clearly defined roles, and robust technological infrastructures to mitigate unnecessary workload burdens.

In contrast, while Process Unsuitability and Documentation Debt were correlated with workload, they were not significant predictors when evaluated alongside other types of PD. This finding suggests that while these types of debt individually affect developers' workload, their overall impact is moderated when other, more critical PD types are addressed effectively.

From a theoretical perspective, this research makes a significant contribution to the existing body of knowledge by clarifying the specific quantitative impacts of different PD types on workload within ASD contexts. Practically, our findings offer targeted guidance for practitioners and organizational leaders seeking to enhance productivity and mitigate workload-related stress. Interventions should prioritize role clarification initiatives, synchronization improvements, and infrastructure investments as core strategies for reducing the detrimental effects of PD.

The novelty of this study lies in its rigorous empirical quantification of how distinct types of PD individually and collectively affect workload within ASD teams. This research thus uniquely contributes to PD literature by providing clear, quantitative differentiation among PD types, thereby offering targeted insights into managing them. Practically, this empirical clarification enables organizations to prioritize interventions effectively to reduce workload pressures. The quantification and comparative analysis offer new empirical insights beyond previous qualitative studies, thereby enriching theoretical understanding and practical applications of PD management in ASD contexts.

This study, however, is subject to certain limitations, including its reliance on cross-sectional data, which may limit causal interpretations, and its exclusive focus on Swedish organizations, which may affect its broader applicability. Future research should employ longitudinal methodologies to assess causality over time and extend data collection across diverse organizational and cultural contexts, thereby enhancing generalizability.

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References

1. Ahmad, M. O., Gustavsson, T., Katin, A., Taušan, N., Mandić, V.: Non-technical aspects of technical debt in the context of large-scale agile development: A qualitative study. In 2024 50th Euromicro Conference on Software Engineering and Advanced Applications (SEAA), pp. 260-267 (2024).
2. Alves NS, Ribeiro LF, Caires V, Mendes TS, Spínola RO. Towards an ontology of terms on technical debt. In: 2014 Sixth International Workshop on Managing Technical Debt 2014; pp. 1-7 (2014).
3. Belsley, D.A.: Conditioning diagnostics: Collinearity and weak data in regression. John Wiley & Sons, Inc, New York (1991).
4. Besker, T., Martini, A., Bosch, J.: Software developer productivity loss due to technical debt—A replication and extension study examining developers' development work. Journal of Systems and Software, 156, 41-61 (2019).
5. Caplan, R. D.: Organizational stress and individual strain: A social psychological study of risk factors in coronary heart disease among administrators, engineers, and scientists. University of Michigan, Ann Arbor (1971).
6. Codabux, Z., Williams, B.: Managing technical debt: an industrial case study. In: 2013 4th International Workshop on Managing Technical Debt (MTD), IEEE, pp. 8–15 (2013).
7. Cohen, J.: Statistical Power Analysis for the Behavioral Sciences, 3rd ed. Routledge, New York (1992).
8. Dybå, T., Dingsøyr, T.: Empirical studies of agile software development: a systematic review. Inf. Softw. Technol. 50 (9–10), 833–859 (2008).
9. Gomes, F., Santos, E., Freire, S., Mendes, T.S., Mendonça, M., Spínola, R.: Investigating the point of view of project management practitioners on technical debt – A study on stack exchange. J. Softw. Eng. Res. Dev., 11(1), 12-1 (2023).
10. Gray-Stanley, J. A., Muramatsu, N.: Work stress, burnout, and social and personal resources among direct care workers. Research in developmental disabilities, 32(3), 1065-1074 (2011).
11. Guveyi, E., Aktas, M. S., Kalipsiz, O.: Human factor on software quality: A systematic literature review. In: Computational Science and Its Applications–ICCSA 2020: 20th International Conference, Cagliari, Italy, July 1–4, 2020, Springer International Publishing, Proceedings, Part IV 20, pp. 918-930, (2020).
12. Gustavsson, T.: Dynamics of Inter-Team Coordination Routines in Large-Scale Agile Software Development. In Proceedings of the 27th European Conference on Information Systems (ECIS), Stockholm & Uppsala, Sweden, June 8-14 (2019).
13. Gustavsson, T., Ahmad, M.O., Saeeda, H.: Development Of a Measurement Instrument for Process Debt Detection in Agile Software Development Organizations. In B. Marcinkowski, A. Przybylek, A. Jarzebowicz, N. Iivari, E. Insfran, M. Lang, H. Linger, & C. Schneider (Eds.), Harnessing Opportunities: Reshaping ISD in the post-COVID-19 and Generative AI Era (ISD2024 Proceedings). Gdansk, Poland: University of Gdansk. (2024).
14. Gustavsson, T., Ahmad, M.O. and Saeeda, H.: Job satisfaction at risk: Measuring the role of process debt in agile software development. Journal of Systems and Software, 222, 112350, (2025).
15. Hair, J.F.J., Black, W.C., Babin, B.J., Anderson, R.E.: Multivariate Data Analysis. New Jersey, Prentice Hall (2010).
16. Holvitie, J., Licorish, S.A., Spínola, R.O., Hyrynsalmi, S., MacDonell, S.G., Mendes, T.S., Leppänen, V.: Technical debt and agile software development practices and processes: An industry practitioner survey. Inf. Softw. Technol., 96, 141–160 (2018).
17. Jovanović, M., Mas, A., Mesquida, A.L., Lalić, B.: Transition of organizational roles in agile transformation process: A grounded theory approach. J. Syst. Softw., 133, 174–194 (2017).
18. Liebel, G., Tichy, M., Knauss, E., Ljungkrantz, O., Stieglbauer, G.: Organisation and communication problems in automotive requirements engineering. Requir. Eng., 23(1), 145–167 (2018).
19. Martini, A., Besker, T., Bosch, J.: Process debt: A first exploration. In: 2020 27th Asia-

Pacific Software Engineering Conference (APSEC). IEEE (2020).
20. Martini, A., Stray, V., Besker, T., Brede, M. N., Bosch, J.: Process Debt: Definition, Risks and Management. Available at SSRN: https://ssrn.com/abstract=4328073 (2023).
21. Martini, A., Stray, V., Moe, N. B.: Technical-, social- and process debt in large-scale agile: an exploratory case-study. In: International Conference on Agile Software Development (pp. 112-119). Springer, Cham (2019).
22. Michels, L. M., Petkova, A., Richter, M., Farley, A., Graziotin, D., Wagner, S.: Overwhelmed software developers. IEEE Software (2024).
23. Meyer, A. N., Barr, E. T., Bird, C., Zimmermann, T.: Today was a good day: The daily life of software developers. IEEE Transactions on Software Engineering, 47(5), 863-880 (2019).
24. Meyer, A.N., Fritz, T., Murphy, G.C., Zimmermann, T.: Software developers' perceptions of productivity. In: Proceedings of the 22nd ACM SIGSOFT International Symposium on Foundations of Software Engineering, pp. 19–29 (2014).
25. Mills, J., Prasad, K.: A comparison of model selection criteria. Econom. Rev., 1(11), 201–234 (1992).
26. Petersen, K., Wohlin, C.: The effect of moving from a plan-driven to an incremental software development approach with agile practices: an industrial case study. Empir. Softw. Eng. 15, 654–693 (2010).
27. Pikkarainen, M., Haikara, J., Salo, O., Abrahamsson, P., Still, J.: The impact of agile practices on communication in software development. Empir. Softw. Eng., 13, 303–337 (2008).
28. Ribeiro, D. M.: Understanding the relationships between the perceptions of burnout and instability in Software Engineering. In: Proceedings of the XXXVI Brazilian Symposium on Software Engineering, pp. 58-67 (2022).
29. Saeeda, H., Ahmad, M. O., Gustavsson, T.: Multivocal Literature Review on Non-Technical Debt in Software Development: An Exploratory Study. ENASE, pp. 89-101, (2023).
30. Scheerer, A., Hildenbrand, T., Kude, T.: Coordination in large-scale agile software development: A multiteam systems perspective. In: 2014 47th Hawaii International Conference on System Sciences, IEEE, pp. 4780–4788 (2014).
31. Storey, M.A., Zimmermann, T., Bird, C., Czerwonka, J., Murphy, B., Kalliamvakou, E.: Towards a theory of software developer job satisfaction and perceived productivity. IEEE Trans. Softw. Eng., 47(10), 2125–2142 (2019).
32. Streiner, D.L.: Starting at the beginning: an introduction to coefficient alpha and internal consistency. J. Pers. Assess. 80 (1), 99–103 (2003).
33. Tulili, T. R., Capiluppi, A., Rastogi, A.: Burnout in software engineering: A systematic mapping study. Information and Software Technology, 155, 107116 (2023).
34. Vishnubhotla, S.D., Mendes, E., Lundberg, L.: Investigating the relationship between personalities and agile team climate of software professionals in a telecom company. Inf. Softw. Technol., 126, 106335 (2020).
35. West, S.G., Finch, J.F., Curran, P.J.: Structural equation models with nonnormal variables: Problems and remedies. In: Hoyle, R.H. (Ed.), Structural Equation Modeling: Concepts, Issues, and Applications, Sage, Newbery Park, CA, pp. 56–75 (1995).
36. Wong, N., Jackson, V., Van Der Hoek, A., Ahmed, I., Schueller, S. M., Reddy, M.: Mental wellbeing at work: Perspectives of software engineers. In: Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems, pp. 1-15 (2023).
37. Young, D.S.: Handbook of Regression Methods. CRC Press, Boca Raton, FL (2017).