Integrating Informal Learning into Deployment Planning and Project Scheduling

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Keywords

Abstract

Dynamic organizations constantly search for new ways to improve the quality of their processes. A core element of these efforts is the integration of informal learning into daily workflows. Interdisciplinary research is required to accomplish this challenging task and make informal learning manageable. In this study, we propose a novel combination of organizational theory and operational research using a quantitative project scheduling approach to create efficient workflows, including systematized informal learning. The concept of integrating the informal learning activities of knowledge sharing, reflection, and self-organization is presented based on a multi-objective, multi-resource constrained project scheduling problem with limited renewable resources, activity splitting, and preemption. Additional simulation studies demonstrate the calculation of informal learning ratios, together with further discussion of strategic management options.

1. Introduction

The advancing digitalization of economic processes requires optimized integration of different management tasks. Furthermore, a crucial characteristic of the Fourth Industrial Revolution is a dynamic change to flatten hierarchies and agile management (Benkenstein et al., 2017). Informal learning is a growing research field that requires an interdisciplinary perspective (Cerasoli et al., 2018). Therefore, organizations that are subject to digital transformation need an understanding of agility and learning that adapts to their organizational type (e.g., functional, matrix, or project-oriented), structure, and culture (Bigelow & Barney, 2021; Claver-Cortés et al., 2012; Verhoef et al., 2021).

Learning is a complex and idiosyncratic internal process involving an individual's cognitive, emotional, and motivational resources (Freigang et al., 2018). However, formal learning, which comprises structured learning content, has weaknesses in promoting further learning (Blume et al., 2010). In contrast, informal learning focuses on individual learning by providing employees control over their learning processes in the workplace (Gulati & Puranam, 2009; Sambrook, 2005). Cerasoli et al. (2018) indicate that up to 90 percent of organizational learning occurs informally rather than through formal training. Consequently, organizations must create and foster conditions that support systematic informal learning, which is characterized as being unstructured and unguided (García-Peñalvo & Conde, 2014).Therefore, integrating informal learning into business processes and systematically measuring possible effects is a challenging management task and a significant success factor (Blit, 2017). This is also highlighted by March (1991), who indicates that proper use of information technology and organizational learning is likely to improve competitive positions.

We consider a systematic integration of informal learning behaviors into operations management, that is, quantitative project scheduling, based on the resource constraint project scheduling problem (RCPSP), presented inter alia by Brucker et al. (1999), Hartmann and Briskorn (2010), Kataoka et al. (2019), and Speranza and Vercellis (1993).The contribution of this study is twofold. First, we extend classical quantitative scheduling to create a multi-objective perspective and include a manageable procedure to incorporate the three informal learning behaviors: (1) knowledge sharing, (2) reflection, and (3) self-organization. Second, we provide a concept for

measuring the impact of informal learning on project performance (Edmondson & Mcmanus, 2007; Sauermann & Stephan, 2013). The resulting novel learning-oriented hybrid scheduling approach provides managers with stable structures to learn exploitation strategies (Fang et al., 2010; Posen & Levinthal, 2012) and helps them develop their businesses toward continuous learning organizations (Greve, 2020).

The remainder of this paper is organized as follows. Section 2 describes the role and possible challenges in managing informal learning. The process of integrating informal learning behaviors into project scheduling and the concept for measuring the effects of informal learning are presented in Section 3. Furthermore, in section 4, we present a mathematical model for informal learning-oriented project scheduling. Insights into the model structure and simulation analysis are provided in Section 5, based on a use case from the IT service industry. Finally, a discussion in Section 6 and conclusions provided in Section 7 conclude the article.

2. The Role of Informal Learning Behaviors

Informal learning promotes employee motivation and participation, and increases job satisfaction as uncertainty is reduced through newly-acquired knowledge and abilities (Zhang et al., 2020). It helps expand experience, and activities can be performed more routinely with fewer errors (Guadalupi, 2018). Thus, informal learning increases performance and allows further learning by fulfilling the three basic psychological needs of competence, relatedness, and autonomy (Ryan & Deci, 2017). From a management perspective, informal learning contains a deficit in that it mostly takes place unintentionally and is, therefore, hardly tangible. Most practical knowledge is inevitably developed in this manner (Cefis et al., 2020; Noe et al., 2010; Shepherd et al., 2014).

Informal learning is highly situation-specific; that is, the learning effect experienced in general routines depends on its context. Thus, it requires abstraction skills at a higher level and the ability to transfer the acquired knowledge to new contexts (Cerasoli et al., 2018). Consequently, the acquired knowledge is not necessarily reflected in the individual's behavior, but in the expanded potential for behavioral flexibility (Hoyle, 2015). Furthermore, the application of new capabilities depends on organizational conditions and individuals' mindset (Jiang et al., 2016). Therefore, in addition to the external aspects of learning, subjective internal aspects are important and can only

be modified under certain conditions (Matsuo, 2019; Tews et al., 2017).

For businesses, it is important to channel informal learning activities, make knowledge available to the entire organization, and build competencies (Zhang et al., 2020). In addition to traditional ways of improving job performance and learning, such as advanced trainings, seminars, and annual reviews with supervisors or formal guidance, organizations should identify new ways to support informal learning. Managers and employees need work schedules that provide a certain level of free space or agility embedded in the overall working process without endangering strategic company goals in terms of customer satisfaction and market position.

Therefore, we intend to create working environments (workflows) that promote informal learning behaviors (Bednall et al., 2014; Thomas et al., 2001). Particularly, the evaluation of learning embedded in social interactions and teams should be made possible (Guadalupi, 2018; Yakhlef, 2010).
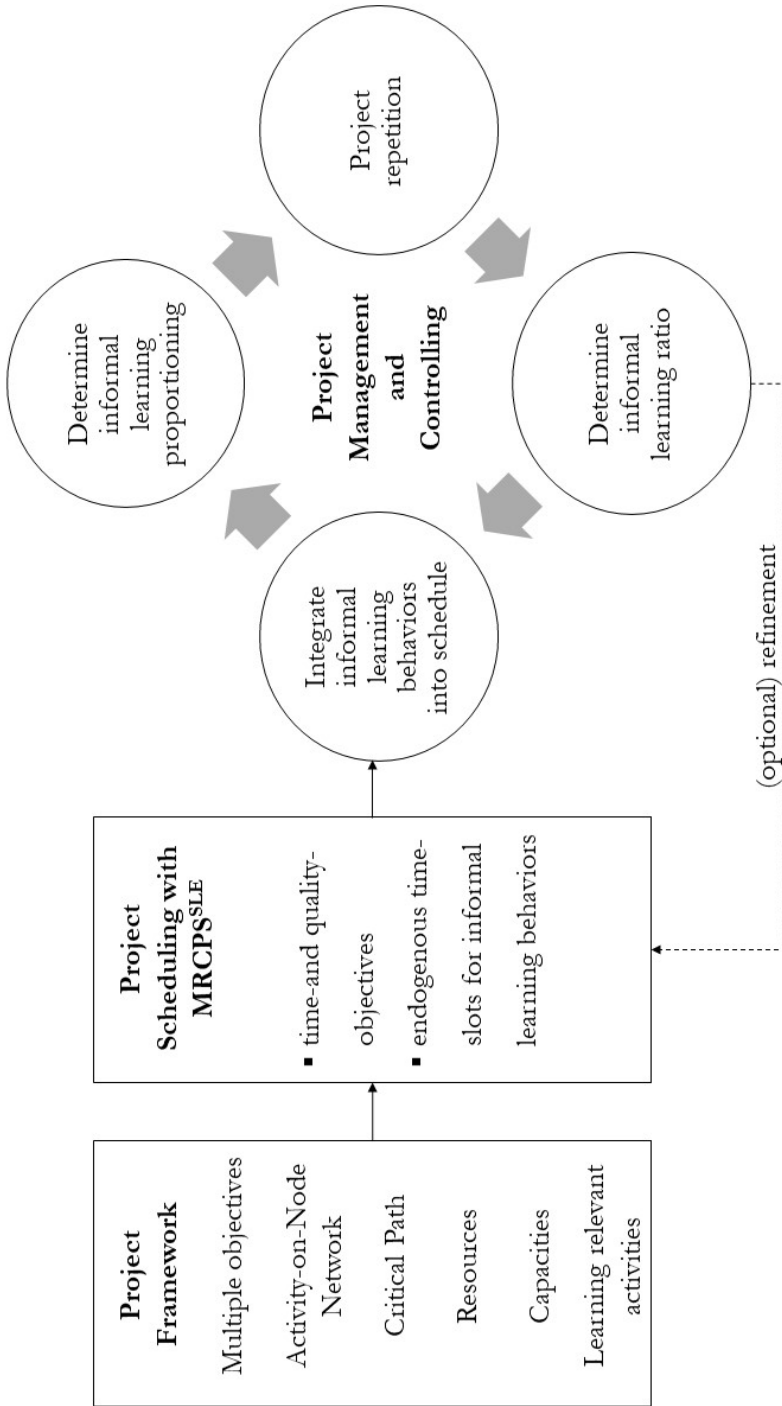
In this context, informal learning behaviors refer to three specific factors: knowledge sharing, reflection, and self-organization (Bednall et al., 2014). We consider complex business projects that characteristically show high potential for (informal) learning based on their dynamic structure (Jahr, 2014). Therefore, we aim to systematize traceable time slots for learning activities in a project schedule and make informal learning manageable (1). However, owing to their complex structure, it is, in principle, not possible to simply add dummy activities for learning to project schedules. Moreover, projects must be cost and time efficient. Consequently, we use operational research to optimize schedules.

3. A Concept for Integrating and Measuring Informal Learning Behaviors in Business Projects

We use a modified operational research algorithm (model MRCPS$^{\text{SLE}}$, see Section 4) to generate optimal project schedules, including optimized time slots that can be used for systematic informal learning activities. Figure 1 shows the process of integrating and measuring informal learning behaviors in optimal project schedules.

First, the project structure is established. Here, we consider a multi-objective approach, including project efficiency, measured by the total project duration, and project quality, which is also time-based, as a proxy for activity efforts. This creates a conflict as both objectives are negatively correlated, that is, increasing project durations indicate increasing efforts and thus qual-

Figure 1: Process of systemizing informal learning in projects

ity, but at the same time decreasing efficiency, which is given by reductions
in project durations. It is important for businesses to optimize efficiency and
quality to meet customer needs. In the mathematical model, strategic ori-
entation is depicted by a target weight $0 \leq w \leq 1$. In the next step, project
activities subject to learning must be identified. The model structure allows
for learning to be assigned to any activity. However, it is more likely that
learning, in particular, occurs in value-adding tasks, such as code program-
ming and software design (see Section 5). Therefore, a learning time slot
factor α is integrated into the activity-shifting constraint. We propose that
this factor is related to the trade-off in the objective function by assuming
a linear functional relationship (1).

$$w = \frac{1}{2}\alpha \tag{1}$$

Based on the weight value range and Equation (1), the time slot factor
$0 \leq \alpha \leq 2$ can maximally force an activity to take twice its duration for
possible learning activities, which is a realistic upper bound for maximum
delays (Jahr, 2014). Additionally, if quality is not considered in a project
run ($w = 0$), then there are no additional explicit time slots for learning,
and the project focus is solely on efficiency ($1 - w$). The optimal schedule
offers different types of time slots for learning activities (Section 4). There-
fore, an adequate type of informal learning behavior depends on the number
of available free resources. For example, if all resources are available in
a scheduled time slice, knowledge-sharing learning formats can be planned
(e.g., Barcamp). In the case of a reduced number of free resources, reflection-
learning formats are possible (e.g., lean coffee or working-out-loud). Finally,
if only individuals are free, they can use self-organized learning formats (dig-
ital internal (wikis) or external company platforms). Hence, the schedule is
complemented by suitable learning time slots that offer identifiable shares of
the total project duration. Consequently, the repeated execution of projects
with similar resources can be monitored by an informal learning ratio (ILR).

$$ILR = \frac{TS_k^{IL}}{TD_k} \cdot 100\% \ \forall k \in K \tag{2}$$

The ILR considers the share of informal learning on total team days (sum
of employees assigned to activities, multiplied with the process times of the

activities) in each project run $k \in K$. Thus, the denominator is the total number of team days in the project. The numerator (3) collects those informal learning time slices in the optimal schedule that extend the considered pure activity durations and, hence, are intended for informal learning activities.

$$TS_k^{IL} = \sum_{j=1}^{IL_J} \sum_{m=1}^{M} [(c_j - s_j) - p_{jm}] \tag{3}$$

The difference between a job completion time and starting time $(c_j - s_j)$ indicates the actual job execution. If the execution time is equal to the job-processing time in modes m, p_{jm}, then there is no extra time in terms of activity-split or preemption (see Section 4). Positive and increasing informal learning ratios between runs $k \in K$ are beneficial in principle. However, next to the ILR, the project duration must be controlled to monitor project efficiency. For example, an increasing numerator at a constant denominator indicates that more time is spent on informal learning activities; that is, more resources (employees) could participate in the format. Simultaneously, if the project duration remains constant, then there is also an indication of learning (curve) effects (Wright, 1936) with a positive impact on efficiency (e.g., Section 5, Table 1, scenario variation $w = 0.6$). By contrast, increasing denominators can decrease the ILR and hence indicate fewer options for employees to participate in informal learning formats. These findings are also in accordance with the learning curve paradigm (Wright, 1936).

4. Learning-Oriented Multi-objective Resource Constrained Project Scheduling

To generate optimal project schedules, we consider relevant types of scheduling models based on the (RCPSP), which is a well-examined and highly complex planning problem (Ballestín et al., 2008; Hartmann & Drexl, 1998). We use the basic formulation introduced by Buddhakulsomsiri and Kim (2006) to provide an easily traceable mathematical formulation. This formulation provides chronological starting and completion times for project activities and includes activity splitting and preemption. However, we extend their model by using four elements. We consider optimizing multiple weighted criteria, taking into account the total project duration and project quality (constraint 4). Furthermore, we incorporate direct resource-to-job assignment (constraint 5) and resource-dependent renewable capacities (constraint 12).

Moreover, we incorporate learning time slot factors (constraint 6). There-
fore, the relationship (1) is not explicitly modelled within a constraint to
maintain a mixed-linear structure and prevent nonlinearity. Thus, the fac-
tors w and a are calculated separately in the process (see Figure 1 and the
Appendix). In this case, the individual learning time slots can be assigned
$\alpha = \sum_{j=1}^{A} \alpha_j$.

A supportive learning environment is defined as a schedule that creates spe-
cific time slots for informal learning activities. These time slots are au-
tomatically assigned via sequencing. Figure 1 shows that the underlying
activity-on-node network (AoN) must identify relevant activities for infor-
mal learning, such as meetings. In this case, the model must ensure that
all resources are assigned to this activity in one time period and, therefore,
book a joint time slot. In addition, capacity constraint scheduling can re-
sult in activity splitting and preemption, thereby creating time slots with
free resources (Razavi & Mozayani, 2007; Vanhoucke & Coelho, 2019; Zare,
2012). Thus, both procedures generate additional free time slots.

However, in addition to providing a feasible and efficient schedule, the model
offers limited possible shifting for manual control. Here, we assume two dif-
ferent simple effort levels (high and low) for service projects, that is, software
projects (Coelho & Vanhoucke, 2011). However, the operation modes can
also be used to represent any technical element. The resulting multiobjec-
tive resource constraint project scheduling for self-organized learning (MR-
CPSSLE) considers multiple objectives, multiple operation modes, limited
renewable resources, activity-splitting, preemption usable for informal learn-
ing activities next to intended meeting activities, and reflection during the
process of an activity and self-organization by directly assigning resources
to jobs. We use the following notations:

Indices

$j \in A$	—	Jobs index and $(i,j) \in V$ precedence relation of jobs i and j
M	—	Operation Modes Index
R	—	Renewable Resources Index
T	—	Time index

Parameters

a_{jrm}	—	The capacity utilization coefficient for job $j \in A$ performed by resource r $\in$ R in mode $m \in M$
α_{jm}	—	Learning slot factor in jobs $j \in A$ in mode $m \in M$
λ_{jrm}	—	Binary parameter to designate whether resource $r \in R$ is able to perform job $j \in A$ ($\lambda_{jrm} = 1$) or not ($\lambda_{jrm} = 0$)
K_{rt}	—	Renewable capacity of resource $r \in R$ in time period $t \in T$
p_{jm}	—	Processing time for job $j \in A$ in operation mode $m \in M$
EST_j	—	Earliest starting time of job $j \in A$
LET_j	—	Latest ending time of job $j \in A$
N	—	Large number or maximum project horizon, respectively
w	—	Objective function weights

Variables

x_{jrmt}	—	Binary variable indicating the actual time periods $t \in T$ in which jobs $j \in A$ are performed in mode $m \in M$ using resource $r \in R$
y_{jm}	—	Binary variable allocation mode $m \in M$ for job $j \in A$
s_j	—	Positive variable indicating starting time of job $j \in A$
c_j	—	Positive variable indicating completion time of job $j \in A$

The Model

The model can then be formulated as follows.

$$\max Z = w * Q - (1 - w) * c_j \tag{4}$$

Subject to

$$\sum_{m=1}^{M} y_{jm} = 1, \quad \forall j \in A \tag{5}$$

$$\sum_{t=1}^{T} x_{jrmt} = p_{jm} (1 + \alpha_{jm}) y_{jm} \lambda_{jrm}, \quad \forall j \in A, r \in R, m \in M \tag{6}$$

$$c_i \leq s_j - 1, \quad \forall (i, j) \in V \tag{7}$$

$$s_j \leq x_{jrmt} * t + N * (1 - x_{jrmt}), \quad \forall j \in A, r \in R, m \in M, t \in T \tag{8}$$

$$c_j \geq x_{jrmt} * t, \quad \forall j \in A, r \in R, m \in M, t \in T \tag{9}$$

$$s_j \geq EST_j - 1, \quad \forall (j) \in A \tag{10}$$

$$c_j \leq LET_j - 1, \quad \forall (j) \in A \tag{11}$$

$$K_{rt} \geq \sum_{j=1}^{A} \sum_{m=1}^{M} a_{jrm} * x_{jrmt}, \quad \forall r \in R, t \in T \tag{12}$$

$$Q = \sum_{j=1}^{A} \sum_{r=1}^{R} \sum_{m=1}^{M} p_{jm} * (1 + \alpha_{jm}) * y_{jm} * \lambda_{jrm} \tag{13}$$

$$x_{jrmt} \in \{0,1\}, \quad \forall j \in A, r \in R, m \in M, t \in T \tag{14}$$

$$y_{jm} \in \{0,1\}, \quad \forall j \in A, m \in M \tag{15}$$

$$s_j \geq 0, \quad \forall j \in A \tag{16}$$

$$c_j \geq 0, \quad \forall j \in A \tag{17}$$

The objective function (4) considers the completion time of the last job c_J and thus, the total project duration or makespan. From the customer (and cost) perspective, shorter completion times are preferred (Liu & Cheng, 2004). We assume that the quality of the project (or product) will increase with a longer total processing time, Q (Chen et al., 2020; Shepherd et al., 2014). Furthermore, employee motivation will probably improve as less time pressure favors an individual's participation in the job (Schaufeli et al., 2009). Hence, the objective function is a weighted multi-criteria function with weights w and $(1 - w)$ seeking efficient alternatives for the opposing goal variables.

As the objective function represents discrete optimization, one must consider that an optimal solution cannot be guaranteed. In fact, it is more likely that only the relevant efficient alternatives are selected using this approach (see Figure 2).Thus, available potentially good compromises may be disregarded by optimization, depending on the weight definition (Olson, 2001; T'kindt & Billaut, 2001). However, the automated calculation of efficient solutions is still a significant benefit compared with the widely used standard manual scheduling (Abedinnia et al., 2017).

Mode allocation condition (5) ensures that a job is performed in only one operation mode, that is, the effort levels for the jobs. Applying less effort to perform a job, and hence, reducing processing times, results in a shorter makespan. This may lead to longer processing times for follow-up rework and troubleshooting. Therefore, the expected quality of the project will decrease if less time is spent performing the project. Therefore, we show a positive correlation between project effort and quality (see Figure 2).

Job distribution condition (6) splits the total job processing time (right-

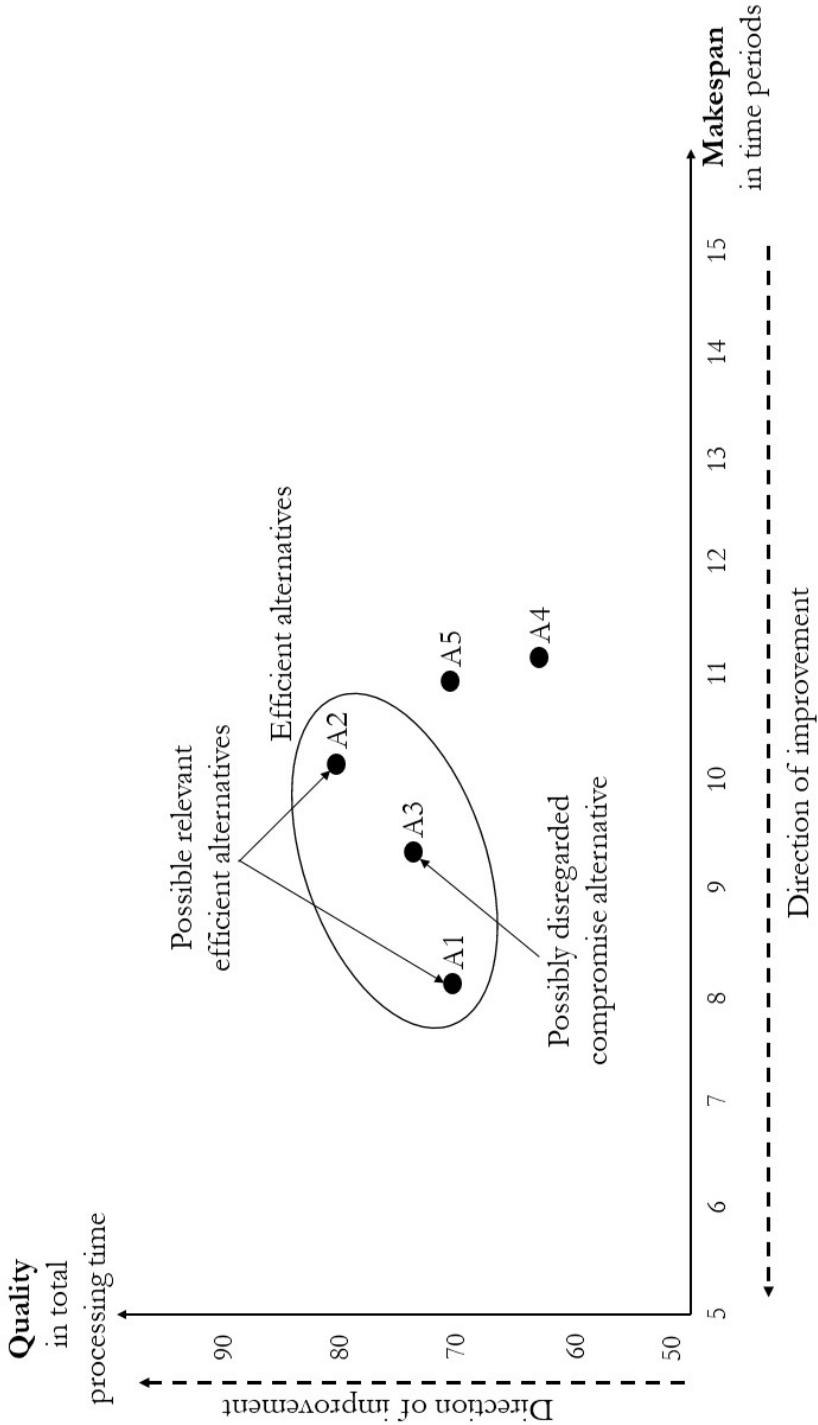Figure 2: Solution space in discrete multicriteria optimization

Figure 3: Job schedule example with job-splitting and preemption

Job name	Processing time	Capacity demand	Time periods			
			t_1	t_2	t_3	T_4
Job_1	2 periods	2 units	$x_{Job1} = 1$ s_{Job1}	$x_{Job1} = 0$ Job-Split	$x_{Job1} = 1$	Preemption c_{Job1}
Total capacity demand (resources)			2	0	2	0

hand side) into parts along the time axis (left-hand side). Accordingly, the activity splitting and preemption of jobs can be depicted in combination with constraints (7) to (11) (Ballestín et al., 2009). Figure 3 shows the basic functions. The positive variables s_j and c_j indicate the time span in which a job can be performed (owing to the model and data structure, they take integer values). However, the time periods within the time span in which the jobs are actually performed are given by the binary variables x_{jrm}, and t. Consequently, a job can be interrupted and resumed within the time interval and/or preempted earlier than the possible completion time. However, each completion of a job requires corresponding capacity units.

Furthermore, in constraint (6), α is added to the processing time. The qualification for a job is considered by the binary parameter λ_{jr}. Assigning only suitable resources is also part of the self-organization aspect. In constraint (7), the sequence relations between jobs are considered (De Reyck & Herroelen, 1999). Hence, the predecessor job i must be completed before successor job j can start. Constraints (8)–(11) ensure that jobs start with their first part before the completion of their last part within the possible time span from the earliest starting time to the latest completion time (Elmaghraby, 1977; Kelley, 1963). In constraint (12), renewable resource capacities are considered so that the processing of a job part does not exceed the available capacities in a specific time period. Constraint (13) is the total processing time, which is a proxy for the project quality. Finally, constraints (14)–(17) define the decision variables.
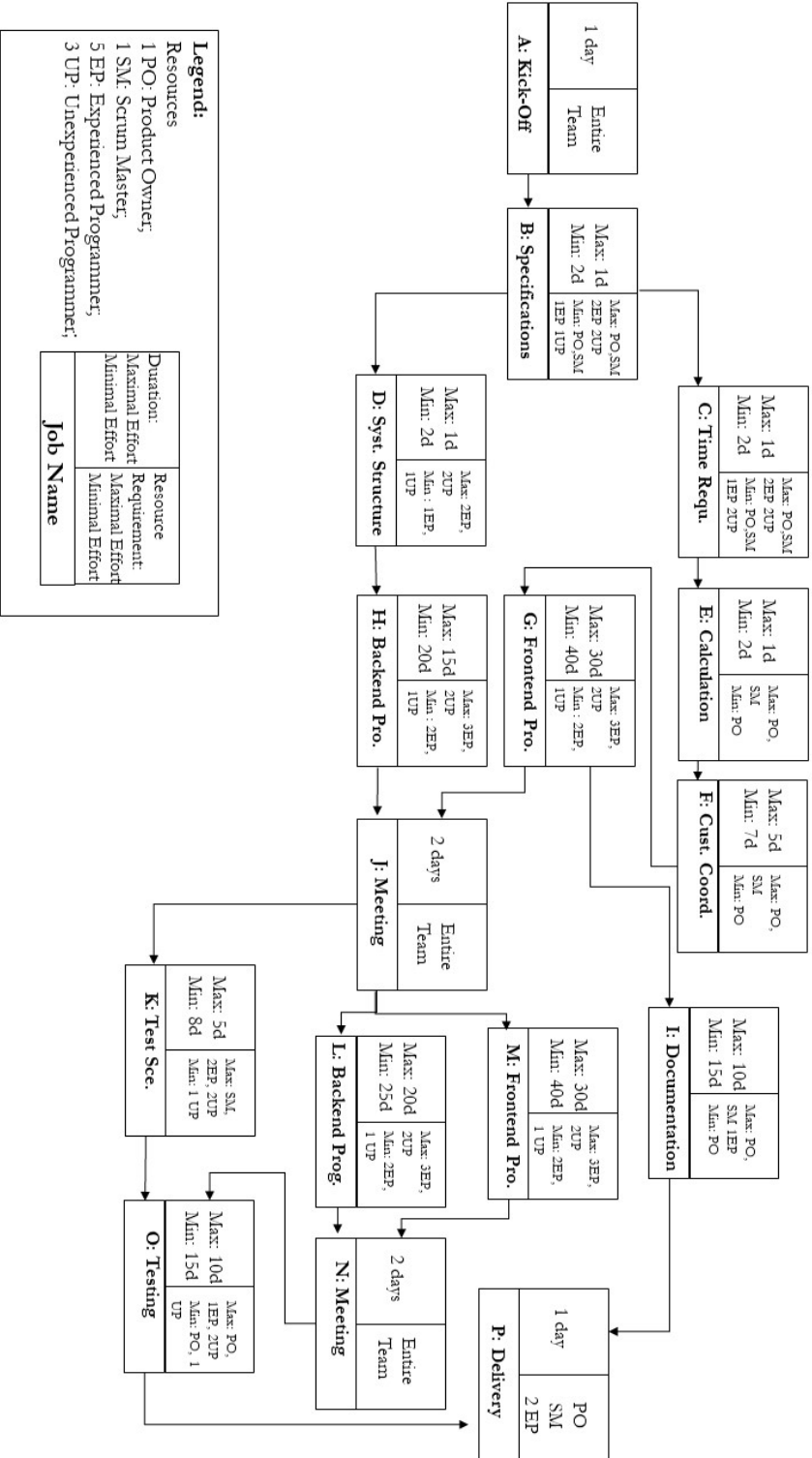
5. Use Case Simulation Study

For the analysis, we consider the real-life use case of a software service provider for customized IT applications with a maximum project horizon of N=135 days (Jahr, 2014). Figure 4 shows the AoN project. After team kick-off, the project specifications and time requirements were determined.

Then, team member-specific jobs are performed, such as budget and scope calculations, customer coordination, and creating the technical system structure. Following the first-level front-end and back-end programming, the first team meeting must be assigned to collect the lessons learned. In the second project phase, the specific jobs are continued, that is, documentation, test scenarios, and second-level programming. Finally, after a second team meeting, software testing and delivery closes the project.

A simulation study including a baseline scenario is used to calculate the project performances, that is, the project durations (PD) or makespans, and the informal learning ratios (see Table 1 and Table 2 and Appendix). Five varying scenarios were compiled for ten alternative variations of weights w and learning factor α in each case. The considered project includes software code programming (frontend and backend) as value-adding activities in early and later project phases, i.e. activities 'G', 'H', 'L' and 'M'. It is likely that (informal) learning has the greatest effect and is used by the company in these activities.

Therefore, simulation scenarios 1 to 5 show different combinations of value-adding activities (see Table 1). The baseline scenario (Scenario 0) reflects a pure multiple objectives resource constraint project scheduling, focusing on project efficiency, that is, minimal project durations without systematic informal learning and thus $w = \alpha = 0$. Scenario 1 includes all value-adding activities and therefore reflects the other 'extreme' ending of the simulation study. The computations of the $MRCPS^{SLE}$ were carried out using GAMS Version 24.8.5, and the SCIP and BARON solvers for mixed integer and nonlinear problems (Kılınç & Sahinidis, 2018; Vigerske & Gleixner, 2018). All calculations were executed on an Intel Core i5 7200U CPU with 8 GB of RAM and 2.71 GHz. Both hardware and software reflect the standard technology in this field.

Most scenarios were solved optimally and within an acceptable timeframe (see Appendix). Consequently, improving computation times using heuristics, such as serial schedule generation schemes (Kolisch & Hartmann, 1999), is not required for the considered simulation scope. However, regarding the general complexity of the problem (Anderson, 1999; Zareei & Hassan-Pour, 2015), larger data sizes might require heuristic procedures (Lova et al., 2006).

Table 1 shows the simulation results as well as the scenario means, standard deviations (SD), and coefficients of variation (variation). In addition, Table

Figure 4: IT project AoN

2 shows the average results for varying weights in scenarios 1 to 5. In all scenarios, a complete focus on quality ($w = 1$) required the total project horizon (N=135).

The baseline scenario shows a certain degree of unsystematic informal learning but at a low level with high volatility, which impedes the structured usage of learning effects. In addition to the ILR, the baseline results, in terms of project duration, are efficient and stable. All other scenarios show project durations at the same higher level because of the systematic informal learning efforts. An interesting effect can be observed between weights $w = 0.7$ and $w = 0.8$. There, the project performance increases, that is, the duration decreases, and informal learning ratios remain stable or even increase. This could indicate possible classic learning (curve) effects for higher quality focuses in the considered test setting.

However, Scenarios 3 and 4, which emphasize informal learning activities in later phases, outperform those with informal learning in earlier stages (scenarios 2 and 5). Furthermore, further analysis of the five core scenarios indicates that 'extreme' scenario 1 promises the best overall project performance while considering informal learning. Thus, one-sided learning activities in the early or later project phases as well as selected

In this sense, the use of all value-adding activities for informal learning behaviors reflects continuous informal learning in a project. This is the best way to reduce project performance volatility and offers stable options for informal learning effects and quality improvements. Regarding the trade-off between quality and efficiency (minimal makespan), a quality focus range of $0.3 \leq w \leq 0.5$ appears to be favorable; that is, the performance volatility is rather low and a stable systematic use of informal learning is available. Therefore, efficiency $(1 - w)$ remains the recommended focus of projects.

The aggregated development of informal learning ratios and project durations compared with the baseline scenario (Figure 5) indicates a smoothing effect for informal learning and partly for makespans. This can be explained by the structure of Equation (6) and the functional relation in Equation (1). A similar effect has been observed in time-series forecasting based on smoothing models (Hyndman & Athanasopoulos, 2021). There, the forecasting factors shift weights between current and historic data and hence smoothen the forecast in time. In our case, varying α-values shifted the project time to informal learning. Simultaneously, the objective function

Table 1: Simulation results for all scenarios and scenario-specific analysis

| Weight | (0) Baseline Scenario | | (1) Total value-adding activities | | (2) First Level Programming | | (3) Second Level Programming | | (4) Mixed Learning 1 Frontend – Backend | | (5) Mixed Learning 2 Backend – Frontend | |
	ILR	PD	ILR	PD	ILR	PD	ILR	PD	ILR	PD	ILR	PD
0.1	0.0554	86	0.1401	101	0.0567	89	0.0734	98	0.0597	97	0.0209	87
0.2	0.0400	86	0.1505	103	0.0696	92	0.0490	91	0.0508	100	0.0573	91
0.3	0.0694	96	0.1404	118	0.0333	105	0.1088	108	0.0711	105	0.0657	108
0.4	0.0974	106	0.1116	122	0.1145	122	0.1042	122	0.0671	122	0.0537	122
0.5	0.0395	106	0.1907	126	0.1068	126	0.1349	126	0.0884	126	0.0977	126
0.6	0.0789	106	0.2036	130	0.1173	130	0.1332	130	0.0873	133	0.0841	130
0.7	0.0974	106	0.2058	134	0.1724	134	0.1630	134	0.1067	135	0.0905	134
0.8	0.0789	106	0.2058	124	0.1009	133	0.1659	128	0.0938	125	0.1009	128
0.9	0.0421	106	0.2058	124	0.1236	134	0.1965	132	0.1091	126	0.1111	134
1.0	0.2000	135	0.2058	135	0.1174	135	0.1914	135	0.1137	135	0.1304	135
Mean	0.0779	104	0.1764	122	0.1013	120	0.1320	120	0.0848	120	0.0812	120
SD	0.0435	13.03	0.0348	11.04	0.0373	17.02	0.0463	14.95	0.0207	13.68	0.0305	17.01
Variation	56.53%	12.54%	19.73%	9.07%	36.81%	14.18%	35.07%	12.42%	24.44%	11.37%	37.49%	14.23%

ILR: Informal Learning Ratio; *PD:* Project Duration; *Weight:* Objective Weight for Quality w

Table 2: Weight Specific Analysis for Simulations of Scenarios 1 to 5

	ILR			PD		
Weight	Mean	SD	Variation	Mean	SD	Variation
0.1	0.0702	0.0309	55.64%	94	5.43	5.75%
0.2	0.0490	0.0382	50.66%	95	5.08	5.33%
0.3	0.1088	0.0371	44.19%	109	4.79	4.40%
0.4	0.1042	0.0249	27.64%	122	0.00	0.00%
0.5	0.1349	0.0369	29.86%	126	0.00	0.00%
0.6	0.1332	0.0434	34.66%	131	1.20	0.92%
0.7	0.1630	0.0438	29.51%	134	0.40	0.30%
0.8	0.1659	0.0447	33.47%	128	3.14	2.46%
0.9	0.1965	0.0428	28.68%	130	4.20	3.23%
1.0	0.1914	0.0389	25.65%	135	0.00	0.00%

ILR: Informal Learning Ratio; *PD*: Project Duration; *Weight*: Objective Weight for Quality w

aims to achieve a trade-off between increasing the time for quality (w) and reducing the time for greater efficiency ($1 - w$). Therefore, the optimization intends to smoothen the project time usage, which is most clear for values $w \geq 0.4$.

By contrast, the ILR in the baseline scenario reacts more strongly to varying weights. Furthermore, there is a strong surge in project duration to full quality focus ($w = 1$) compared to the smoothed aggregated scenarios. In this respect, the model is easier to predict and offers improved planning reliability. In conclusion, the simulation indicates that informal learning can be systematically integrated into project scheduling and simultaneously provide reliable project performance. The strategic implications remain a focus on efficiency ($w \leq 0.5$) with continuous usage of informal learning in all relevant value-adding activities, up to 10% of the available resource time.

6. Discussion

According to Ryan and Deci (2017), social integration into an organization, is one of the basic psychological needs of employees, such as social support or collectivity. Therefore, it is important to generate optimal project schedules to enable employee participation in informal learning activities. Our approach systematically incorporates informal learning into project scheduling, making informal learning behaviors identifiable.
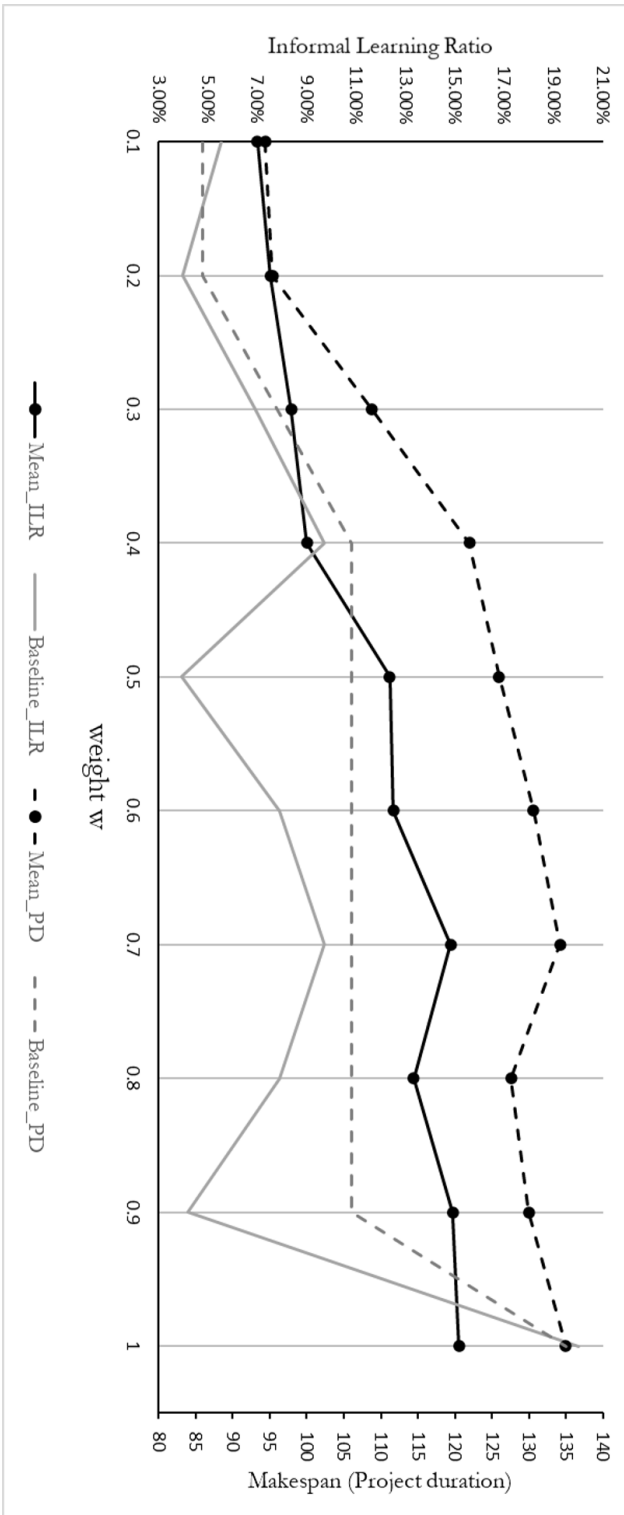
Figure 5: ILR and PD development of the baseline scenario and average of scenarios 1 to 5

However, a crucial point when transferring real-life system elements into an abstracting mathematical model is the accurate mapping of qualitative aspects into quantitative parameters (Nasrallah et al., 2003). Here, the representation of informal learning behaviors shows a limited theoretical accuracy of psychological processes. Nevertheless, we show that the systemization of informal learning allows for the application of mathematical modelling. The considered approach intends to make efficiency-oriented management more flexible and adaptive to the way individuals collaborate and perform their work in the B2B and B2C contexts.

In this context, a lively discussion focused on innovative organizational methodology in the early 2000s, that is, traditional versus agile management (Heimicke et al., 2020; Jahr, 2014; Schmidt, 2019). Following this discussion in recent years, observers have obtained the impression that they represent opposing sides or philosophies of business management. On the one hand, traditional management is based on fixed structures and scheduling, hierarchical decision-making, and control, which focus on customer demands, particularly by meeting delivery times, quantities, and prices, that is, costs or budgets. In this traditional management environment, relatively broad qualitative and quantitative methods have been available and continuously refined for a long time.

On the other hand, there is a relatively-new agile methodology that focuses on employee needs with flat hierarchies and flexible work schemes. This approach is beneficial to employee motivation and, therefore, has a positive effect on process and product quality (Carbonell et al., 2009). However, the encounter of customers and upper management expectations about fixed budgets and times, and employee expectations about free space while performing their tasks is a constant source of conflict.

It could be argued that both worlds are not completely contrary; for example, the agile SCRUM project management concept is not agile in the way that it was initially meant to be (*Manifesto for Agile Software Development*, 2001), but an interpretation of traditional project management with enhanced free space for employees. The strongest reference to this view is the fact that the editors of the agile manifesto withdrew their philosophy some years later, following the above lines of argument (*Manifesto for Half-Arsed Agile Software Development*, 2001). Here, we do not intend to expand on the discussion. We recognize that business managers, especially in the

service industry, face the challenge of keeping up with innovative agile management approaches in an area of tension between markets, stakeholders, and shareholders.

7. Conclusions

Knowledge creation is a key task at the center of strategic management decisions. Therefore, learning has become a competitive factor for organizations to improve their performances and sustain their market position. However, organizational learning is largely informal and thus organizations require efficient methodology to make informal learning calculable.

The objective of this study is the systematization and integration of informal learning into daily project workflows. We show that hybrid approaches combining artificial intelligence and agile organizational theory can be used to balance strategic efficiency and quality based goals. Thus, providing opportunities to learn within an organization can lead to increased commitment of an individual and team, which in turn helps increase employee retention (Neininger et al., 2010). Furthermore, the approach implicitly aims at an individual's self-efficacy, which describes people's inner conviction to achieve greater professionalism through their own abilities and actions (Alt & Raichel, 2020). Another important aspect is the quantification of the causes and effects of informal learning. Here, we propose an informal learning ratio that quantifies the informal learning options for employees within a project.

A simulation study shows that up to 10% of the working time can be used for informal learning activities within projects at acceptable project durations compared to a baseline scenario. Moreover, stable (or decreasing) project durations and increasing ILR can indicate learning effects, as described by Wright (1936). This study also revealed that classic efficiency-oriented management is recommended as the dominant strategic option. Nevertheless, new organizational aspects can be considered without significantly increasing project efficiency. Consequently, we present an enhanced multiobjective resource constraint project scheduling model to integrate systematic time slots for informal learning and agile elements into efficiency-based operations management.

There is considerable need for research on the application of hybrid approaches in agile management and digitalization, notably in the service industry. For example, Benkenstein et al. (2017) indicated that operational

research methodologies are increasingly being used in the service industry. Hence, broad-based empirical studies and economic experiments focusing on the specifications of model variables and parameters can refine the accuracy of the presented scheduling in strategic management. Moreover, a large amount of traditional operational research and new agile concepts can be combined and extended to solve the current problems in various business areas.

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