

D Microscopy Conclusion2



I am writing a discussion for my PhD Thesis. I want you to write me a conclusion on the microscopy part of this work. I will provide you with results and summarizing discussion. It is latex code, please also output in latex. Also, please understand the key takeaways from both results but also from the potentials and challenges discussed in the summarising discussion, and summarise them in the conclusion. Please also provide a clear and comprehensive title for the conclusion.

\subsubsection*{\INA Cells Saturate hMSC-Interaction to Proliferate into Aggregates} %%%

hMSCs are isolated as a heterogeneous cell population. To analyze whether \INA cells could adhere to every hMSC, we saturated hMSCs with \INA. A seeding ratio of 1:4 (hMSC:\INA) resulted in the occupation of \SIplusminus{93}{6}{\percent} of single hMSCs by one or more \INA cells within 24 hours after \INA addition, escalating to \SI{6}{\percent} after \SI{48}{\hours} (\autoref{fig:1}A, B). Therefore, most hMSCs provide an interaction surface for \INA cells.

INA-6 exhibits homotypic aggregation when cultured alone, a phenomenon observed in some freshly isolated myeloma samples (up to \SI{100}{cells} after \SI{6}{hours})

\cite{kawanoHomotypicCellAggregations1991,okunoVitroGrowthPattern1991}. Adding hMSCs at a 1:1 ratio led to smaller aggregates after \SI{24}{hours} (size \SIrange{1}{5}{cells}), all of which were distributed over \SIplusminus{52}{2}{\percent} of all hMSCs (\autoref{fig:1}A, B). Intriguingly, \INA aggregation was notably absent when grown on confluent hMSCs, and occurred only when heterotypic interactions were limited to 0.2 hMSCs per \INA cell (\autoref{fig:1}C). We concluded that \INA cells prioritize heterotypic over homotypic interactions.

To monitor the formation of such aggregates, we conducted live-cell imaging of hMSC/\INA co-cultures for \SI\{63\{\text{hours}\}. We observed that \INA cells adhered long after cytokinesis, constituting \SIplusminus\{55\{12\{\text{hours}\}, increasing to more than \SI\{75\{\text{hours}\} for the remainder of the co-culture (\autoref\{fig:1\}D). Therefore, homotypic \INA aggregates were mostly formed by cell division.

\subsubsection*{Apoptosis of \INA Depends on Ratio Between Heterotypic and Homotypic Interaction}

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Although direct interaction with hMSCs has been shown to enhance myeloma cell survival through NF-\$\kappa\$B signaling

\cite{hideshimaUnderstandingMultipleMyeloma2007}, the impact of aggregation on myeloma cell viability during hMSC interaction remains unclear. To address this,



we measured the cell viability (ATP) and apoptosis rates of \INA cells growing as homotypic aggregates compared to those in heterotypic interactions with hMSCs by modulating hMSC density (\autoref{fig:1}E). To equalize the background signaling caused by soluble MSC-derived factors, all cultures were incubated in hMSC-conditioned medium and the results were normalized to \INA cells cultured without direct hMSC contact (\autoref{fig:1}E,\,left).

varying group sizes. Technical replicates = three per datapoint; 100 single

hMSCs were evaluated per technical replicate.

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\tile{C} Interaction of INA-6 with hMSCs at different hMSC densities (constant INA-6 densities). Scale bar = \SI{300}{\um}. \tile{D} Two types of homotypic interaction: Attachment after cell contact and sustained attachment of daughter cells after cell division. Datapoints represent one of four independent time-lapse recordings, each evaluating 116 interaction events. \tile{E} Effects of hMSC-density on the viability (ATP, top) and apoptosis (Caspase3/7 activity, bottom). INA-6:MSC ratio = 4:1; \mbox{Technical replicates = four per datapoint}; \tile{E},left} Signals were measured in INA-6 washed off from hMSCs and normalized by INA-6 cultured in MSC-conditioned medium (\$= \text{red line}\$) (\$n=4\$). \tile{E},right} Signals were measured in co-cultures and normalized by the sum of the signals measured in hMSC and INA-6 cultured separately (\$= \text{red line}\$) (\$n=3\$). \tile{Statistics} Paired t-test, two-factor RM- ANOVA. Datapoints represent independent co-cultures with hMSCs from three (A, B, D, E\,right), four (E\,left) unique donors. Confl.\,=\,Confluent. }

\INA viability (ATP) was not affected by the direct adhesion of hMSCs at any density. However, apoptosis rates decreased over time \omnibus{F}{2,6}{23.29}{-unc}{\scinot{1.49}{-3}} (Two-factor RM-ANOVA), interacting significantly with MSC density \omnibus{F}{4,12}{6.98}{-unc}{\scinot{3.83}{-3}} For example, 24 hours of adhesion to confluent MSCs increased apoptosis rates by \SIplusminus{1.46}{0.37}{fold}, while culturing \INA cells on dispersed hMSCs (ratio 1:1) did not change the apoptosis rate (\SIplusminus{1.01}{0.26}{fold}).



We presumed that sensitive apoptotic cells might have been lost when harvesting \INA cells from hMSCs. Hence, we measured survival parameters in the co-culture and in hMSC and \INA cells cultured separately (\autoref{fig:1}E,\,right). We defined MSC interaction effects when the survival measured in the co-culture differed from the sum of the signals measured from \INA and hMSCs alone. RM-ANOVA confirmed that adherence to confluent MSCs increased apoptosis rates of \INA cells \SI{24}{hours} after adhesion and decreased after \SI{72}{hours} \omnibus{F}{2,4}{26.86}{-unc}{\scinot{4.80}{-3}} (interaction between MSC density and time, Two-factor RM-ANOVA), whereas \INA cells were unaffected when grown on dispersed hMSCs.

In summary, the growth conformation of \INA cells, measured as the ratio between homotypic aggregation and heterotypic MSC interactions, affected apoptosis rates of \INA cells.

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%	==	Timelapse
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\subsubsection*{Single \INA Cells Detach Spontaneously from Aggregates of Critical Size} %%%

Using time-lapse microscopy, we observed that \SIplusminus{26}{8}{\percent} of \INA aggregates growing on single hMSCs spontaneously shed \INA cells (\autoref{fig:2}A, B; Supplementary\,Video\,1). Notably, all detached cells exhibited similar directional movements, suggesting entrainment in convective streams generated by temperature gradients within the incubation chamber. \INA predominantly detached from other \INA cells or aggregates (\autoref{fig:2}C), indicating weaker adhesive forces in homotypic interactions than in heterotypic interactions. The detachment frequency increased after \SI{52}{hours}, when most aggregates that shed \INA cells were categorized as large (greater than 30 cells) (\autoref{fig:2}D). Since approximately 10-20 \INA cells already fully covered a single hMSC, we suggest that myeloma cell detachment depended not only on hMSC saturation but also required a minimum aggregate size. Interestingly, \INA detached mostly as single cells, independent of aggregate size categories \omnibus{F}{2,6}{4.68}{-unc}{0.059}

(Two-factor RM-ANOVA) (\autoref{fig:2}E), showing that aggregates remained mostly stable despite losing cells.

Time-lapse analysis of INA-6 detachment from INA-6 aggregates and hMSCs. \tile{A} Frequency of observed INA-6 aggregates that did or did not lose INA-6 cell(s). 87 aggregates were evaluated per datapoint. \tile{B} Example of a ``disseminating'' INA-6 aggregate growing on fluorescently (PKH26)



stained hMSC (from A-D). Dashed green lines are trajectories of detached INA-6 cells. Scale bar = \SI{50}{\um}. \tile{\umbox{C-E}} Quantitative assessment of INA-6 detachments. 45 detachment events were evaluated per datapoint. Seeding ratio INA-6:MSC = 4:1. \tile{C} Most INA-6 cells dissociated from another INA-6 cell and not from an hMSC \umbbox \umbbox

\vspace{-.3cm}

\subsubsection*{Cell Division Generates a Daughter Cell Detached from hMSC} %%%

We suspected that cell division drives detachment because we observed that MSC-adhering \INA cells could generate daughter cells that "roll over" the mother cell (\autoref{fig:3}A; Supplementary\,Video\,2). We recorded and categorized the movement of \INA daughter cells in confluent hMSCs after cell division. Half of all \INA divisions yielded two daughter cells that remained stationary, indicating hMSC adherence (\autoref{fig:3}B,\,C; Supplementary\,Video\,3). The other half of division events generated one hMSC-adhering cell and one non-hMSC-adhering cell, which rolled around the \MAina cell for a median time of \SI{2.5}{hours} post division (Q1=\SI{1.00}{hour}, Q3=\SI{6.25}{hours}) until it stopped and re-adhered to the hMSC monolayer (\autoref{fig:3}D; Supplementary\,Video\,2, Supplementary\,Video\,2, Supplementary\,Video\,4). Thus, cell division establishes a time window in which one daughter cell can detach.

Detachment of INA-6 daughter cells after Cell Division. \tile{A-D} INA-6 divisions in interaction with confluent hMSCs. Seeding ratio INA-6:MSC = 4:20. \tile{A} Three examples of dividing INA-6 cells generating either two MA, or one MA and one nMA daughter cells as described in (G). Dashed circles mark mother cells (white), MA cell (blue), and first position of nMA cell (green). Scale bar: \SI{20}{\umblum}. \tile{B} Cell division of \ac{MA} mother cell can yield one mobile \ac{nMA} daughter cell.

\tile{C} Frequencies of INA-6 pairs defined in (A, B) per observed cell division. 65 divisions were evaluated for each of three independent time-lapse recordings. \tile{D} Rolling duration of nMA cells after division did not depend on hMSC donor \omnibus{H}{2}{5.250}{-unc}{.072}.

Datapoints represent single nMA-cells after division. \tile{E-G} Adhesive and cell cycle assessment of MSC-interacting INA-6 subpopulations using the



V-Well assay. \tile{E} Schematic of V-Well Assay (see \apdxref{apdx:supplemental}{fig:S1} for detailed analysis). MSC-interacting subpopulations were separated by subsequent centrifugation and removal of the pellet. The pellet size was quantified by its total fluorescence brightness. Adhering subpopulations were resuspended by rough pipetting. \tile{F} Relative cell pellet sizes of adhesive INA-6 subpopulations that cycle either asynchronously or were synchronized at mitosis. Gray lines in-between points connect dependent measurements of co-cultures (\$n=9\$) that shared the same hMSC-donor and INA-6 culture. Co-cultures were incubated for three different durations (\SIlist{1;2;3}{\hour} after INA-6 addition). Time points were pooled, since time did not show an effect on cell adhesion \omnibus{F}{2,4}{1.414}-unc}{0.343}

Factorial RM-ANOVA shows an interaction between cell cycle and the kind of adhesive subpopulation \omnibus{F}{1,8}{42.67}{-unc}{\scinot{1.82}{-4}}. Technical replicates = 4 per datapoint. \tile{G} Cell cycles were profiled in cells gathered from the pellets of four independent co-cultures (\$n=4\$) and the frequency of G0/G1 cells are displayed depending on co-culture duration (see \apdxref{apdx:supplemental}{fig:S3} for cell cycle profiles). Four technical replicates were pooled after pelleting. \tile{Statistics} (D): Kruskal-Wallis H-test. (F): Paired t-test, (G): Paired t-test, two-factor RM-ANOVA. Datapoints represent INA-6 from independent co-cultures with hMSCs from three unique donors.

To validate that cell division reduced adhesion, we measured both the size and cell cycle profile of the \nMAina and \MAina populations using an enhanced V-well assay (method described in \autoref{fig:3}E,

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\apdxref{apdx:supplemental}{fig:S1},\,\ref{fig:S2}). For comparison, we fully synchronized and arrested \INA cells at mitosis and released their cell cycle immediately before addition to the hMSC monolayer, rendering them more likely to divide while adhering. Mitotic arrest significantly increased the number of \nMAina cells and decreased the number of \MAina cells (\autoref{fig:3}F). Furthermore, the \nMAina population contained significantly more cells cycling in the G0/G1 phase than the \MAina population, both in synchronously and asynchronously cycling \INA (\autoref{fig:3}G,

\apdxref{apdx:supplemental}{fig:S3},\,\ref{fig:S4}\). The number of \nMAina \INA cells increased due to a higher cell division frequency. Taken together, we showed that \INA detach from aggregates by generating one temporarily detached daughter cell after cell division, a process that potentially contributes to the initiation of dissemination.



\label{sec:discussion_potential_breakthroughs}%

Exploratory experimentation emphasizes discovering and characterizing novel phenomena \cite{mattigClassifyingExploratoryExperimentation2022}. Exploratory cell biology often leverages emerging technologies to visualize and analyze the mechanisms of cell behavior dynamically. Such approaches allow real-time observations that can lead to unexpected insights and breakthroughs. In this project, the application of live-cell imaging proved pivotal.

\textbf{Direct Observation of Complexity and Novelty:}
Initially, the project did not focus on \textit{in vitro} myeloma cell
dissemination. The project's research focus shifted when making the unexpected
\dashedsentence{or argueably insignificant} observation of cancer cells
detaching from aggregates. This shows the transformative power of time-lapse
microscopy or live cell imaging \cite{coleLivecellImaging2014}. For the author,
live-cell imaging provides an observation method that's unmatched in intuition
and directness. Unlike RNA sequencing, which can obscure biological processes
behind cryptic data, live-cell imaging offers a clear view into the dynamic
cellular events as they unfold.

Such clarity was particularly effective in revealing the detachment of cells following division, a phenomenon that might be overlooked in static analyses. Multiple parameters can be read out in parallel, such as both time and aggregate size for detachments to begin. Also, complex cellular behavior can be deduced from movement, or rather lack thereof, which was interpreted as re-attachment of \INA daughter cells to the \ac{hMSC} monolayer. This allowed for measuring the duration of \nMAina existing until re-attaching and turning into \MAina. This information was helpful when designing experiments to prove that dissemination is initiated by cell division, requiring precise timing to capture the detached daughter cells right after cell division. Together, live cell imaging enabled key mechanistic insights in understanding the dynamics involved in multicellular interactions by integrating the study of multiple phenomena at once.

\textbf{Difficulties Connecting Observation with Acedemic Terminology} Exploring video data begins with the search of scientific novelties. In order to correctly identify cellular phenomena relevant to the research question, a deep understanding of cell biology is required, e.g. in field of cell dynamics to read migratory behavior \cite{nalbantExploratoryCellDynamics2018}. This is a challenge for both students and experienced researchers, since finding the academically correct terms to describe observations is difficult, especially for novel phenomena or a sequence of events that can overlap. After all, cell biology is taught using textbooks, not videos. For this project in particular, the used terminology was revised frequently, being caused by the constant struggle of finding the middle-ground between the precice description of observations, the compatibility with results from other experiments, comprehensability, and memorability. Ultimately, comprehensability and memorability were prioritized to maximize adoption of the new terminology by other researchers. For instance, \emph{non MSC adherence} was chosen over \emph{mobile interaction}, \emph{aggregation} over \emph{homotypic interaction}, and \emph{detachment event} over \emph{in vitro metastasis}. In general, the gap between observations and their description remains a challenge in exploratory cell biology that might be overlooked. This gap could be bridged by currently



available multimodal \acp{LLM} like \texttt{ChatGPT-4o}: These models could match recorded phenomena with descriptions and images that were amassed in the literature over decades. By doing so, researchers not only use established terminology instead of inventing new terms, but also minimize the risk of missing potential discoveries.

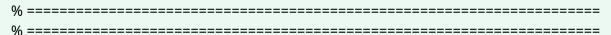
\textbf{Why Hide Videos Behind a Download Link?} A major challenge remains in how to effectively present these dynamic observations in a publishable format, as traditional scientific publications and websites are not equipped to display video data. Instead, it is common practice to assemble video frames into static figures, presumably to support both online and printed reading habits \cite{perasDigitalPaperReading2023}. Representative example videos are then relegated to supplementary data. Although supplementary data is downloaded often, most biomedical researchers favor a presentation of additional figures and tables directly on the journal's website

\cite{priceRoleSupplementaryMaterial2018}. Given the increasing availability of video data\footnote{The number of \texttt{PubMed} articles with \emph{``live cell

imaging"} doubled from 2011 to 2023.}, embedding video content next to figures and tables on the article's website does make a compelling case. In fact, the journal \emph{\text{Nature}} does offer this feature already, but rarely used \cite{\text{NatureVideoContent}}. In the end, there is no reason to not present videos alongsife figures and tables, as they can be as informative, and potentially more so. Such new standards can benefit other fields of medicine, as videos provide the best medium for first aid, medical emergency and education \cite{\text{guptaDatasetMedicalInstructional2023}}.

Overall, Live-cell imaging has proven indispensable in exploratory cell biology, uncovering dynamic cellular phenomena that static analyses often miss. This is exemplified in this work, where live-cell imaging shifted the research focus by revealing unexpected cell behaviors, like detachment during division, emphasizing the need for integrating real-time observations with molecular data. By making such dynamic processes visible, live-cell imaging not only enriches our understanding but also challenges us to enhance how scientific findings are presented, advocating for greater accessibility of video data in scientific publications.

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\unnsubsection{Potential and Challenges of Image Cytometry}%
\label{sec:discussion_quantifying_microscopy}%
Quantifying microscopy data is critical for both analytic and exploratory
approaches to microscopy: For instance, microscopic assessment of live/dead
cells should produce bar charts presenting cell viabilities
\cite{spaepenDigitalImageProcessing2011}, whereas describing novel phenomena
should be supported by charts proving the reproducibility of claimed
observations. Microscopy data is source of vast amount and types of information:
cell morphology; organelle count, shape, and distribution; membrane and lipid
distribution; protein localization, DNA content, et cetera. However, leveraging



this information has always been limited by the ability to extract quantitative data from microscopy images \cite{galbraithPumpingVolume2023}. This extraction process is the essence of \emph{image cytometry}, a field that has seen significant advances by integrating machine learning for automating image analysis tasks. \cite{guptaDeepLearningImage2019}. The following sections discuss the experiences gained from this project in quantifying microscopy data and outlines potentials and challenges of image cytometry.

Nextbf{Considering Automated Analysis for Future Live-Cell Imaging:}
This work would have benefited from
computational automation for the analysis of live-cell imaging, for example, the
task of associating \INA cell detachment with \INA aggregate size and time:
Manual analysis consisted of zooming in closely and
watching the time-lapse over and over again until a detachment event was found.
A very tedious task that had to be repeated approx. 50 times for every one of
four independent videos. Instead of manually counting the number of single \INA
cells across time, a pixel segmentation algorithm could have been trained to
detect cells and background. Single cells would be discernable from aggregates
by filtering cells by size. The count of single cells would then be
representative of detached cells, given that the vast majority of INA6 cells
were part of aggregates.

\def\imagefeatures{%

\emph{Features} are structural elements of an image, such as edges, corners, directions, colors. These features are mathematically extractable using \emph{filters} \dashedsentence{also referred to as \emph{convolution}

kernels}}, which are functions or algorithms applied to the pixel values of an image. For instance, \emph{gabor filters} can extract edges of one particular direction, resulting in an image of the same size as the input, but showing only edges of one direction. \emph{Feature extraction} is the process of applying multiple filters, resulting in a stack of filtered images called a feature vector. \cite{szeliskiFeatureDetectionMatching2011, guptaDeepLearningImage2019}}

\def\cnn{%

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\emph{Convolutional neural networks} (CNN) are algorithms that use the output of a feature extractor\footref{foot:image_features} to feed into a neural network. The network then learns to associate these feature vectors with a label, such as \emph{cell} or \emph{background}. This is called \emph{supervised learning}.

The workload of manual video analysis motivated the purchase of \texttt{Intellesis}, a software package by \textit{Zeiss} for the \texttt{Zen} microscopy software ecosystem. \texttt{Intellesis} is a machine learning-based pixel segmentation software \cite{ZeissOADFeature}. As a feature



extractor\footnote{\label{foot:image_features}\imagefeatures}, it uses the first convolution layers of VGG19, which is convolutional neural network\footnote{\cnn} \cite{\simonyanVeryDeepConvolutional2015}. \texttt{Intellesis} does not contain a deep neural network for segmentation, but instead classifies pixel features using a \emph{\random forest classifier}. Random forest is a machine learning algorithm that \dashedsentence{\for small sets of training images} performs almost as well as deep neural networks, but are computationally far less demanding \cite{\breimanRandomForests2001, richardsonDenseNeuralNetwork2023}. A comparable hybrid approach was also used by \citet{\qamarHybridCNNRandomForest2023} to segment images of bacterial spores into eight distinct pixel classes using only 50 training images. Also, free alternatives to \texttt{Intellesis} exist, such as Ilastik \cite{\bergIlastikInteractiveMachine2019}.

\texttt{Intellesis} proved useful for segmenting single multi-channel images. However, live cell imaging adds another layer of complexity to image analysis: The addition of a time axis encodes the motion of objects and other image features. This concept can be described with the term \emph{optical flow} \cite{niehorsterOpticFlowHistory2021}. Mathematically speaking, optical flow is a vector field that describes the motion of image features\footref{foot:image_features} between consecutive frames of a video. It can be used to train machine learning models on video data efficiently \cite{robitailleSelfsupervisedMachineLearning2022}. Without tricks like optical flow, machine learning algorithms like \texttt{Intellesis} segment the video frame by frame, ignoring the feature similarities between frames. This makes segmentation computationally inefficient, but not impossible \cite{pylvanainenLivecellImagingDeep2023}.

Together, future analyses of live-cell imaging data could benefit from the use of modern machine learning based tools that have been released recently, as summarised in \citet{pylvanainenLivecellImagingDeep2023}.

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In this study, image cytometry was indispensable for validating prior cell divisions within the \nMAina cell population by profiling their DNA content. The complexity of this experiment required a method capable of managing a high throughput across three subpopulations, four timepoints, and two conditions, involving up to 24 samples per trial (\apdxref{subapdx:figs}{fig:S3}). Despite having access to automated \ac{FACS} equipment offered by the Core Unit FACS at the University of Würzburg, the author saw a more time- and cost-effective solution in the laboratory microscope equipped with motorized stage top and \texttt{Intellesis}. This setup scanned 96 different samples in \SI{1.5}{\hour}, and resulting large scans were processed by \texttt{Intellesis} overnight, quantifying thousands of DNA-stained nuclei. This demonstrated that image cytometry could match the throughput and precision of \ac{FACS} with modern standard microscopy equipment (\apdxref{subapdx:figs}{fig:S2}).

The advantages of image cytometry could have of great impact for the future of



cell biology: It is applicable to adherent cell cultures \cite{roukosCellCycleStaging2015} and provides diverse readouts like structure, brightness, size, and shape. Moreover, image cytometry's capacity to evaluate cell viability without the need for staining or expensive analytical chemicals makes it an exceptionally cost-efficient approach for drug screening, reducing operational costs to cell culturing and electricity for microscopy \cite{pattaroneLearningDeepFeatures2021}. However, challenges such as the need for sophisticated automation in microscopic scans, including autofocus and shading adjustments, and the computational demands of AI processing remain.

Interestingly, the author's initial unfamiliarity with image cytometry and limited experience in image processing did not prevent the effective use of this technology. This underscores the accessibility of current imaging tools to biologists without specialized training in image analysis. As confirmed by recent advancements \cite{nittaRapidHighthroughputCell2023}, image cytometry is becoming increasingly competitive with established techniques like \ac{FACS}. Despite its limitations, the simplicity and efficiency of image cytometry could be pivotal for its broader acceptance and integration into biological research. The exclusivity of \textit{Intellesis} to \textit{Zeiss} microscopes could be a major hurdle, however there are free alternatives offering the same accessibility \cite{bergIlastikInteractiveMachine2019}.

\textbf{Manual Analysis Remains Robust for Complex and Unique Phenomena:} Many biologists lack the access to tools like \texttt{Intellesis}, or the computational expertise to automate analysis of microscopy data, often reverting to manual analysis. This project also utilized manual strategies for the detailed characterization of dynamic intercellular interactions such as attachment, aggregation, detachment, and division. This was very time-consuming and required a thoughtful categorization strategy and a disciplined, bias-free execution. However, some analysis tasks are simply unfeasable for automation. For example, this work manually counted if two \INA cells interacted homotypically due to coming into contact with each other, or by staying connected as two daughter cells after cell division. Automating such a task would require a very sophisticated algorithm and developing such would be unfeasable for a task that unique. Hence, manual analysis is unmatched in terms of flexibility and complexity of categorizations, when compared to computational techniques of image processing.

In summary, image cytometry significantly enhanced this project by merging the precision of \ac{FACS} with the cost-efficiency of modern microscopy. Utilizing \texttt{Intellesis} simplified complex image analyses, making advanced cytometric techniques more accessible. While challenges like automation and software availability persist, the potential of image cytometry to advance

biomedical research and discovery remains substantial.

\unnsubsection{Technical Considerations for Image Cytometry}% \label{sec:discussion_quantifying_microscopy}%

\textbf{Acquiring Accurate Image Data:}

In order to capture rare cellular events with a frequency sufficient for statistical analysis, this study chose high temporal resolution and spatial depth: We utilized \SI{1}{frame} every \SI{15}{\minute}, suitable for tracking cell migration \cite{huthSignificantlyImprovedPrecision2010}, but too slow for intricate movements or intracellular processes. Spatial resolution is a compromise between detail and the total observed surface area. We favored the latter to allow the exploration of potentially rare events, and acquired a \dashedsentence{somewhat arbitrarily} large surface area of up to \SI{13}{\milli\meter\squared}. Ultimately, we assessed only approx. a quarter of the acuired surface area, as that was sufficient to gather enough events for each time bin. Such extensive automated video acquisition poses high demands on microscopy equipment, including an incubation setup and motorized stage top. The total size of video files can also complicate storage, transfer and analysis. The raw video data from chapter 1 comprises \SI{80}{GB} \cite{biostudiesBioStudiesEuropeanBioinformatics}; however, far more data was acquired due to protocol optimizations and treatments not shown in this work. File size could have been reduced by acquiring in an 8-bit image format, although a larger bit-depth could be necessary for precise and/or sensitive fluorescence microscopy. Minimizing the acquired surface area could have reduced file size as well, however the meniskus of the medium led to significant shading effects that complicated the choice of the surface area for phase contrasting. Also, archiving large surface scans allows for the search of very rare events in the course of future projects. After all, HDD space is cheap, while re-acquiring data is not. Hence, exploratory live



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\section{Conclusion: Integrative Insights from Live-Cell Imaging and Image Cytometry in \INA and hMSC Interactions}

This study's microscopy component provided pivotal insights into the dynamics of \INA and hMSC interactions. Through a combination of live-cell imaging and advanced image cytometry, several key conclusions were drawn, enhancing our understanding of myeloma cell behavior and the implications for therapeutic strategies.

\subsection*{\INA Cells Exhibit Specific Interaction Preferences with hMSCs} \INA cells demonstrated a pronounced preference for adhering to hMSCs over forming homotypic aggregates. This was evidenced by a high initial attachment rate of \INA cells to hMSCs, which further facilitated the formation of smaller and more dispersed aggregates. Such behavior underscores the critical role of hMSCs in modulating myeloma



cell organization and suggests that targeting these interactions could influence disease progression and treatment outcomes.

\subsection*{Dynamic Observations of Cell Detachment and Reattachment} Live-cell imaging revealed that \INA cells detach from aggregates primarily after reaching a critical size and subsequently exhibit movement suggestive of convection-induced migration. This detachment process is significantly influenced by cell division, where daughter cells demonstrate varied adherence behavior. This highlights a potential mechanism for myeloma cell dissemination, emphasizing the need for therapies that can modulate these cellular interactions and prevent metastasis.

\subsection*{Cell Viability and Apoptosis Influenced by Interaction Context} Quantitative microscopy demonstrated that \INA cell viability was unaffected by direct hMSC adhesion, but apoptosis rates varied significantly based on the density of hMSC interaction. This indicates that the cellular microenvironment and specific interaction contexts critically influence cell survival. Understanding these nuances is essential for developing interventions that target the tumor microenvironment to reduce myeloma cell survival.

\subsection*{Challenges and Advancements in Image Cytometry}
The project highlighted the substantial benefits and some limitations of image cytometry.
The manual analysis provided robustness and flexibility necessary for complex
categorization tasks, while automated image analysis tools like \texttt{Intellesis} were
invaluable for high-throughput quantification. Future research would benefit from
integrating more advanced machine learning algorithms to handle the dynamic and
multifaceted data generated from live-cell imaging.

\subsection*{Implications for Future Research and Clinical Applications}
The findings underscore the transformative potential of live-cell imaging in providing real-time insights into cellular dynamics that static methods cannot capture. The detachment and reattachment behaviors observed in \INA cells suggest mechanisms for cancer dissemination that could be targeted in therapeutic strategies. Furthermore, the use of image cytometry for precise, high-throughput data analysis promises to enhance the resolution and speed of future cellular research.

In summary, this study's microscopy-based approach not only elucidated key aspects of \INA and hMSC interactions but also showcased the potential of integrating live-cell imaging with quantitative image cytometry. These methodologies offer a powerful platform for exploring cellular behaviors in real-time and with high precision, paving the way for new therapeutic targets and enhanced understanding of cellular dynamics in cancer biology.

This conclusion summarizes the key findings and implications from the microscopy component of your PhD thesis, emphasizing the insights gained from the dynamic and quantitative analysis of cell interactions. It highlights the transformative impact of live-cell imaging and the benefits and challenges of image cytometry, while also pointing to future research directions and clinical applications.



It's a good start, but you will have to compress that into three paragraphs at most.



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\section{Conclusion: Integrative Insights from Live-Cell Imaging and Image Cytometry in \INA and hMSC Interactions}

This study leveraged live-cell imaging and image cytometry to unravel the dynamic interactions between \INA cells and hMSCs, revealing critical insights into myeloma cell behavior. \INA cells demonstrated a pronounced preference for adhering to hMSCs over forming homotypic aggregates, underscoring the significant role of the tumor



microenvironment in modulating cell organization. This interaction not only facilitated smaller, dispersed aggregates but also influenced cell viability and apoptosis rates, highlighting the impact of cellular context on myeloma cell survival.

Live-cell imaging provided a unique perspective on the dynamic processes of \INA cell detachment and reattachment, particularly following cell division. This detachment, which increased after aggregates reached a critical size, suggests a mechanism for potential myeloma cell dissemination. The findings emphasize the importance of real-time observation in capturing cellular behaviors that are pivotal for understanding disease progression and developing targeted therapies.

Quantitative image cytometry proved invaluable for high-throughput analysis, enabling precise measurement of cellular interactions and viability. The integration of manual and automated techniques facilitated comprehensive data analysis, though challenges such as automation and computational demands remain. This study underscores the potential of these advanced imaging techniques in enhancing our understanding of cellular dynamics and highlights their role in driving future research and therapeutic innovations.

This revised conclusion compresses the key points into three paragraphs while retaining the essential insights and implications from the microscopy component of your research.



Can you remove some of the exact results, but rather include more of how the overall potentials and challenges impacted this work?



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\section{Conclusion: Integrative Insights from Live-Cell Imaging and Image Cytometry in \INA and hMSC Interactions}

This study utilized live-cell imaging and image cytometry to investigate the complex interactions between \INA cells and hMSCs, offering significant insights into myeloma cell behavior. The findings underscored the critical role of the tumor microenvironment in shaping cell behavior, where \INA cells showed a preference for heterotypic interactions with hMSCs. These techniques revealed dynamic processes, such as cell detachment and migration, which are pivotal for understanding disease mechanisms and developing therapeutic strategies.

Live-cell imaging proved instrumental in capturing real-time cellular behaviors that static methods cannot, such as the detachment of \INA cells during division. This ability to directly observe dynamic processes provided a deeper understanding of the cellular mechanisms that may contribute to myeloma dissemination. However, this approach also posed challenges, including the need for extensive manual analysis and the difficulty of presenting dynamic data in traditional scientific formats, highlighting the potential benefits of integrating automated analysis tools in future research.

Image cytometry facilitated high-throughput and precise analysis of cellular interactions, despite challenges related to automation and computational demands. The integration of manual and automated techniques in this study not only enabled a comprehensive analysis but also demonstrated the accessibility and potential of these advanced imaging technologies for broader applications in biomedical research. These findings underscore the importance of adopting innovative imaging techniques to enhance our understanding of cellular dynamics and inform the development of new therapeutic interventions.

This revised conclusion focuses more on the broader impacts and challenges of using live-cell imaging and image cytometry, without delving into specific results. It highlights how these methodologies influenced the study and their potential implications for future research.





I do like that! Can you implement these keywords without increasing the overall size of this conclusion?: Machine learning



latex

\section{Conclusion: Integrative Insights from Live-Cell Imaging and Image Cytometry in \INA and hMSC Interactions}

This study utilized live-cell imaging and image cytometry, augmented by machine learning, to investigate the complex interactions between \INA cells and hMSCs, offering significant insights into myeloma cell behavior. The findings underscored the critical role of the tumor microenvironment in shaping cell behavior, where \INA cells showed a preference for heterotypic interactions with hMSCs. These advanced techniques revealed dynamic processes, such as cell detachment and migration, which are pivotal for understanding disease mechanisms and developing therapeutic strategies.

Live-cell imaging proved instrumental in capturing real-time cellular behaviors that static methods cannot, such as the detachment of \INA cells during division. This ability to directly observe dynamic processes provided a deeper understanding of the cellular mechanisms that may contribute to myeloma dissemination. However, this approach also posed challenges, including the need for extensive manual analysis and the difficulty of presenting dynamic data in traditional scientific formats. The integration of machine learning for image analysis can streamline future research by automating the detection of complex cellular events, addressing these challenges effectively.

Image cytometry facilitated high-throughput and precise analysis of cellular interactions, despite challenges related to automation and computational demands. The use of machine learning enhanced data processing capabilities, enabling a more comprehensive analysis. This study demonstrated the accessibility and potential of these advanced imaging technologies for broader applications in biomedical research. The findings underscore the importance of adopting innovative imaging techniques and machine learning to enhance our understanding of cellular dynamics and inform the development of new therapeutic interventions.

This version includes references to machine learning and highlights its role in enhancing data processing and analysis without increasing the overall size of the conclusion.



Do you think there are better titles for this conclusion? One that integrates automation, the evident potential of image cytometry?



Certainly! Here are some alternative titles that highlight the key aspects of automation and the potential of image cytometry:

1. "Harnessing Automation and Image Cytometry for Advanced Insights into \INA and hMSC Dynamics"



- 2. "Innovative Approaches in Image Cytometry and Automation: Insights into \INA and hMSC Interactions"
- 3. "Automated Image Cytometry Unveils Dynamic \INA and hMSC Interactions"
- 4. "Leveraging Automated Imaging and Cytometry to Explore \INA and hMSC Cellular Dynamics"
- 5. "Automation and Image Cytometry: Uncovering Critical Dynamics in \INA and hMSC Interactions"

Here's how the conclusion might look with a new title:

latex

\section{Harnessing Automation and Image Cytometry for Advanced Insights into \INA and hMSC Dynamics}

This study utilized live-cell imaging and image cytometry, augmented by machine learning, to investigate the complex interactions between \INA cells and hMSCs, offering significant insights into myeloma cell behavior. The findings underscored the critical role of the tumor microenvironment in shaping cell behavior, where \INA cells showed a preference for heterotypic interactions with hMSCs. These advanced techniques revealed dynamic processes, such as cell detachment and migration, which are pivotal for understanding disease mechanisms and developing therapeutic strategies.

Live-cell imaging proved instrumental in capturing real-time cellular behaviors that static methods cannot, such as the detachment of \INA cells during division. This ability to directly observe dynamic processes provided a deeper understanding of the cellular mechanisms that may contribute to myeloma dissemination. However, this approach also posed challenges, including the need for extensive manual analysis and the difficulty of presenting dynamic data in traditional scientific formats. The integration of machine learning for image analysis can streamline future research by automating the detection of complex cellular events, addressing these challenges effectively.

Image cytometry facilitated high-throughput and precise analysis of cellular interactions, despite challenges related to automation and computational demands. The use of machine learning enhanced data processing capabilities, enabling a more comprehensive analysis. This study demonstrated the accessibility and potential of these advanced imaging technologies for broader applications in biomedical research. The findings underscore the importance of adopting innovative imaging techniques and machine learning to enhance our understanding of cellular dynamics and inform the development of new therapeutic interventions.

This title emphasizes the use of automation and the potential of image cytometry, aligning with the focus of the conclusion.



I reworked the section, do you like it?

\unnsubsection{\textit{\textbf{Conclusion\,1:} Harnessing Automated Microscopy for Exploring Complexity}}%

\label{sec:discussion conclusion microscopy}%

This study utilized live-cell imaging and image cytometry to investigate the complex interactions between \INA cells and hMSCs, offering significant insights into myeloma cell behavior. The findings underscored the critical role of MSC-interactions in shaping cell behavior, e.g. \INA cells showed a preference for heterotypic interactions with hMSCs. These techniques revealed dynamic processes, such as cell detachment and migration, which are pivotal for



understanding disease mechanisms and developing therapeutic strategies.

Live-cell imaging proved instrumental in capturing real-time cellular behaviors that static methods cannot, such as the detachment of \INA cells during division. This ability to directly observe dynamic processes provided a deeper understanding of the cellular mechanisms that may contribute to myeloma dissemination. However, this approach also posed challenges, including the need for extensive manual analysis and the difficulty of extracting quantitative data from image observations and presenting dynamic data in traditional scientific formats. This highlights the potential benefits of integrating automated analysis tools in future research.

Image cytometry facilitated high-throughput and precise analysis of cellular interactions, despite challenges related to automation and computational demands. Combining both manual and automated techniques in this study enabled complex and work-intensive analyses, respectively. A major surprise was accessibility and availability of live-cell imaging equipment and machine learning software, making one hope for a broader adoption in biomedical research and exciting new discoveries.

These findings underscore a current fashion of adopting innovative imaging techniques to enhance our understanding of complex cellular dynamics and multicellular interactions, as previous decades were limited to traditional and static approaches.



Your reworked section is clear and effectively summarizes the key aspects of your study, emphasizing the significance of live-cell imaging and image cytometry. Here are some suggestions to refine it further:

- 1. **Clarity and Specificity**: Some phrases could be more specific, and a few areas could be clearer to strengthen the impact.
- 2. **Focus on Key Points**: Highlight the most important findings and implications more directly.
- 3. **Grammar and Flow**: Minor tweaks for readability and grammar can enhance the overall flow.

Here is the revised section with these considerations:



Live-cell imaging proved instrumental in capturing real-time cellular behaviors that static methods cannot, such as the detachment of \INA cells during division. This capability to observe dynamic processes directly provided a deeper understanding of the cellular mechanisms that may contribute to myeloma dissemination. However, this approach also posed challenges, including the need for extensive manual analysis and the difficulty of extracting quantitative data from image observations. Additionally, presenting dynamic data in traditional scientific formats remains challenging. These limitations underscore the potential benefits of integrating automated analysis tools in future research to streamline and enhance data analysis.

Image cytometry facilitated high-throughput and precise analysis of cellular interactions, despite challenges related to automation and computational demands. The combination of manual and automated techniques in this study enabled the handling of complex and labor-intensive analyses efficiently. A major finding was the accessibility and availability of live-cell imaging equipment and machine learning software, which suggests a promising broader adoption in biomedical research, potentially leading to new discoveries.

These findings underscore the emerging trend of adopting innovative imaging techniques to enhance our understanding of complex cellular dynamics and multicellular interactions. This trend represents a significant advancement over the limitations of traditional and static approaches that dominated previous decades.

Key Changes:

- **Clarity**: Made sentences more specific and clear, e.g., specifying "heterotypic interactions with hMSCs over homotypic aggregation."
- **Focus on Key Points**: Emphasized the most significant findings and their implications for future research.
- **Grammar and Flow**: Improved sentence structure and flow for better readability.

This refined version should make your conclusions more impactful and easier to understand, while maintaining the original meaning and detail.



For the first few lines, can you help me with phrasing? This study utilized two methods that rely heavily on both hardware- and software

automation: Live-cell imaging and image cytometry. Using these methods investigated the complex interactions between \INA cells and hMSCs, offering significant insights into myeloma cell behavior.



Certainly! Here's a refined version of those lines:

latex

This study employed two methods that rely heavily on both hardware and software automation: live-cell imaging and image cytometry. These methods were instrumental in investigating the complex interactions between \INA cells and hMSCs, providing significant insights

complex interactions between \INA cells and hMSCs, providing significant insights into myeloma cell behavior.



Breakdown of the Changes:

- "Employed" instead of "utilized": "Employed" is more direct and commonly used in scientific writing.
- **Simplified the phrase**: "that rely heavily on both hardware and software automation" is more straightforward.
- "These methods were instrumental in": Adds emphasis on the importance of the methods.
- "Providing significant insights": Directly states the contribution of the methods.

This phrasing maintains clarity and emphasizes the significance of both the techniques and the insights gained from the study.



Ok, here's a revised version. When giving feedback, can you point me right to the lines where revision is needed?

\unnsubsection{\textit{\textbf{Conclusion\,1:} Automating Microscopy, an Emerging Trend for Exploring Novel Complexities?}}% \label{sec:discussion conclusion microscopy}%

This study employed two methods that rely heavily on both hardware and software automation: live-cell imaging and image cytometry. These methods were instrumental in investigating the complex interactions between \INA cells and hMSCs, offering significant insights into myeloma cell behavior. The findings underscored the critical role of MSC-interactions in shaping cell behavior, e.g. \INA cells showed a preference for heterotypic interactions with hMSCs. These techniques revealed dynamic processes, such as cell detachment and migration, which are pivotal for understanding disease mechanisms.

Live-cell imaging proved instrumental in capturing real-time cellular behaviors that static methods cannot, such as the detachment of \INA cells during division. This ability to directly observe dynamic processes provided a deeper understanding of the cellular mechanisms that may contribute to myeloma dissemination. However, this approach also posed challenges, including the need for extensive manual analysis and the difficulty of identifying observed phenomena, extracting quantitative data from images and presenting dynamic data in traditional scientific formats. These limitations underscore the potential benefits of integrating automation and machine learning in future research to streamline and enhance data analysis

\cite{guptaDeepLearningImage2019,chengFrontiersDevelopmentLivecell2023}.

Image cytometry facilitated high-throughput and precise analysis of cellular interactions, despite challenges related to automation and computational demands. Combining both manual and automated techniques in this study enabled complex and work-intensive analyses, respectively. A major surprise was accessibility and availability of live-cell imaging equipment and machine learning software, which suggests a promising broader adoption in biomedical research, potentially leading to new discoveries.



These findings underscore a potentially emerging of innovative imaging techniques to enhance our understanding of complex cellular dynamics and multicellular interactions. This trend represents a significant advancement over the limitations of traditional and static approaches that dominated previous decades.



Your revised version is clear and well-organized, but there are a few areas where phrasing and clarity can be improved. I'll point out the specific lines and provide suggestions for each.

Line-by-Line Feedback:

1. Lines 3-4:

- **Current**: "These methods were instrumental in investigating the complex interactions between \INA cells and hMSCs, offering significant insights into myeloma cell behavior."
- **Suggestion**: Simplify and clarify the impact.
- **Revised**: "These methods were crucial for examining the complex interactions between \INA cells and hMSCs, providing significant insights into myeloma cell behavior."

2. Lines 5-7:

- **Current**: "The findings underscored the critical role of MSC-interactions in shaping cell behavior, e.g. \INA cells showed a preference for heterotypic interactions with hMSCs."
- **Suggestion**: Avoid using "e.g." in formal writing and clarify the meaning.
- Revised: "The findings highlighted the critical role of MSC interactions in influencing cell behavior, such as the observed preference of \INA cells for heterotypic interactions with hMSCs."

3. Lines 8-9:

- **Current**: "These techniques revealed dynamic processes, such as cell detachment and migration, which are pivotal for understanding disease mechanisms."
- **Suggestion**: Clarify that "these techniques" refers to live-cell imaging and image cytometry.
- **Revised**: "Live-cell imaging and image cytometry revealed dynamic processes, such as cell detachment and migration, which are essential for understanding disease mechanisms."

4. Lines 12-15:

- Current: "This ability to directly observe dynamic processes provided a deeper
 understanding of the cellular mechanisms that may contribute to myeloma dissemination.
 However, this approach also posed challenges, including the need for extensive manual
 analysis and the difficulty of identifying observed phenomena, extracting quantitative data
 from images and presenting dynamic data in traditional scientific formats."
- Suggestion: Break into two sentences for better readability and clarify challenges.
- Revised: "This capability to directly observe dynamic processes provided a deeper understanding of the cellular mechanisms that may contribute to myeloma dissemination. However, it also presented challenges, such as the extensive manual analysis required, difficulties in identifying observed phenomena, and the complexities of extracting quantitative data and presenting dynamic observations in traditional formats."

5. **Lines 16-18**:

 Current: "These limitations underscore the potential benefits of integrating automation and machine learning in future research to streamline and enhance data analysis \cite{guptaDeepLearningImage2019,chengFrontiersDevelopmentLivecell2023}."



- **Suggestion**: Emphasize the potential of automation and machine learning.
- Revised: "These limitations highlight the potential benefits of incorporating automation and machine learning in future research to streamline and improve data analysis \cite{guptaDeepLearningImage2019,chengFrontiersDevelopmentLivecell2023}."

6. Lines 19-21:

- **Current**: "Image cytometry facilitated high-throughput and precise analysis of cellular interactions, despite challenges related to automation and computational demands."
- **Suggestion**: Specify the nature of challenges.
- Revised: "Image cytometry enabled high-throughput and precise analysis of cellular interactions, even though it faced challenges related to automation and computational requirements."

7. Lines 22-24:

- **Current**: "Combining both manual and automated techniques in this study enabled complex and work-intensive analyses, respectively."
- **Suggestion**: Clarify the benefits of combining manual and automated techniques.
- Revised: "The integration of manual and automated techniques in this study facilitated complex analyses, combining the precision of automation with the flexibility of manual approaches."

8. Lines 24-26:

- Current: "A major surprise was accessibility and availability of live-cell imaging equipment and machine learning software, which suggests a promising broader adoption in biomedical research, potentially leading to new discoveries."
- **Suggestion**: Rephrase for clarity and to avoid passive voice.
- Revised: "The accessibility and availability of live-cell imaging equipment and machine learning software suggest a promising potential for broader adoption in biomedical research, which could lead to new discoveries."

9. Lines 27-29:

- Current: "These findings underscore a potentially emerging of innovative imaging techniques to enhance our understanding of complex cellular dynamics and multicellular interactions."
- o Suggestion: Correct grammar and make the statement more direct.
- Revised: "These findings underscore the emerging trend of using innovative imaging techniques to enhance our understanding of complex cellular dynamics and multicellular interactions."

10. Lines 29-31:

- **Current**: "This trend represents a significant advancement over the limitations of traditional and static approaches that dominated previous decades."
- **Suggestion**: Strengthen the concluding statement.
- **Revised**: "This trend marks a significant advancement over the traditional and static approaches that have dominated research in previous decades."

Here is the revised version incorporating these suggestions:



hMSCs, providing significant insights into myeloma cell behavior. The findings highlighted the critical role of MSC interactions in influencing cell behavior, such as the observed preference of \INA cells for heterotypic interactions with hMSCs. Live-cell imaging and image cytometry revealed dynamic processes, such as cell detachment and migration, which are essential for understanding disease mechanisms.

Live-cell imaging proved instrumental in capturing real-time cellular behaviors that static methods cannot, such as the detachment of \INA cells during division. This capability to directly observe dynamic processes provided a deeper understanding of the cellular mechanisms that may contribute to myeloma dissemination. However, it also presented challenges, such as the extensive manual analysis required, difficulties in identifying observed phenomena, and the complexities of extracting quantitative data and presenting dynamic observations in traditional formats. These limitations highlight the potential benefits of incorporating automation and machine learning in future research to streamline and improve data analysis \cite{guptaDeepLearningImage2019,chengFrontiersDevelopmentLivecell2023}.

Image cytometry enabled high-throughput and precise analysis of cellular interactions, even though it faced challenges related to automation and computational requirements. The integration of manual and automated techniques in this study facilitated complex analyses, combining the precision of automation with the flexibility of manual approaches. The accessibility and availability of live-cell imaging equipment and machine learning software suggest a promising potential for broader adoption in biomedical research, which could lead to new discoveries.

These findings underscore the emerging trend of using innovative imaging techniques to enhance our understanding of complex cellular dynamics and multicellular interactions. This trend marks a significant advancement over the traditional and static approaches that have dominated research in previous decades.

This should ensure clarity, conciseness, and a strong emphasis on the emerging trends in the field.



Ok, I implemented some changes and your revision:

\label{sec:discussion conclusion microscopy}%

This study employed two methods that rely heavily on both hard- and software automation: live-cell imaging and image cytometry. These methods were instrumental in investigating the complex interactions between \INA cells and hMSCs, offering significant insights into myeloma cell behavior. The findings underscored the critical role of MSC-interactions in shaping cell behavior, for instance the observed preference of \INA cells for heterotypic interactions with hMSCs. Live-cell imaging and image cytometry revealed dynamic processes, such as \INA cell growing into clonal aggregates and subsequent cell detachments. These processes are pivotal for understanding disease mechanisms like dissemination.

Live-cell imaging proved instrumental in capturing real-time cellular behaviors that static methods cannot, such as the detachment of \INA cells during division. This ability to directly observe dynamic processes provided a deeper understanding of the cellular mechanisms that may contribute to myeloma dissemination. However, it also presented challenges, such as the extensive manual analysis required, difficulties in identifying observed phenomena, and the complexities of extracting quantitative data and presenting dynamic observations in traditional scientific formats. These limitations highlight the potential benefits of incorporating automation and machine learning in future research to streamline data analysis \cite{guptaDeepLearningImage2019, chengFrontiersDevelopmentLivecell2023}.

Image cytometry facilitated high-throughput and precise analysis of cellular interactions, despite challenges related to automation and computational requirements. The integration of manual and automated techniques in this study facilitated complex analyses, combining the precision of automation with the flexibility of manual approaches. The accessibility and availability of live-cell imaging equipment and machine learning software suggest a promising potential for broader adoption in biomedical research. This could lead to new discoveries of complex cellular dynamics and multicellular interactions.

These findings underscore a potentially emerging trend of innovative imaging and analyses techniques which could be driven my machine learning. This trend marks a significant advancement over the traditional and static approaches that have dominated research in previous decades



Your latest revision is well-formulated and addresses many of the earlier suggestions effectively. Here are a few minor tweaks to further refine clarity and coherence:

- 1. Lines 2-3: Small phrasing improvement for readability.
 - **Current**: "This study employed two methods that rely heavily on both hard- and software automation..."
 - **Suggestion**: "This study employed two methods that heavily rely on both hardware and software automation..."
- 2. **Line 5**: For clarity and to avoid redundancy.
 - Current: "The findings underscored the critical role of MSC-interactions in shaping cell behavior, for instance the observed preference of \INA cells for heterotypic interactions with hMSCs."
 - Suggestion: "The findings underscored the critical role of MSC interactions in shaping cell behavior, particularly the observed preference of \INA cells for heterotypic interactions with hMSCs."
- 3. **Lines 6-7**: Clarify the scientific terms and processes.
 - Current: "\INA cell growing into clonal aggregates and subsequent cell detachments."
 - **Suggestion**: "Processes such as \INA cells forming clonal aggregates and subsequently detaching."
- 4. Lines 12-13: Improve flow and readability.
 - **Current**: "This ability to directly observe dynamic processes provided a deeper understanding of the cellular mechanisms that may contribute to myeloma dissemination."
 - Suggestion: "The ability to directly observe these dynamic processes enriched our understanding of the cellular mechanisms potentially contributing to myeloma dissemination."
- 5. Lines 20-21: Streamline sentence structure.
 - Current: "The accessibility and availability of live-cell imaging equipment and machine learning software suggest a promising potential for broader adoption in biomedical research."
 - Suggestion: "The accessible and available live-cell imaging equipment and machine learning software hold promising potential for broader adoption in biomedical research."
- 6. Lines 23-25: Adjust to ensure grammatical correctness and clarity.



- **Current**: "These findings underscore a potentially emerging trend of innovative imaging and analyses techniques which could be driven my machine learning."
- **Suggestion**: "These findings underscore the emergence of a trend driven by innovative imaging and analysis techniques, potentially powered by machine learning."
- 7. Lines 25-26: Smooth out the conclusion for impact.
 - **Current**: "This trend marks a significant advancement over the traditional and static approaches that have dominated research in previous decades."
 - **Suggestion**: "This trend represents a significant shift from the traditional and static approaches that have long dominated research."

Here's how the paragraph could look with these suggestions:

latex

\label{sec:discussion_conclusion_microscopy}%
This study employed two methods that heavily rely on both hardware and software automation: live-cell imaging and image cytometry. These methods were instrumental in investigating the complex interactions between \INA cells and hMSCs, offering significant insights into myeloma cell behavior. The findings underscored the critical role of MSC interactions in shaping cell behavior, particularly the observed preference of \INA cells for heterotypic interactions with hMSCs. Live-cell imaging and image cytometry revealed dynamic processes, such as \INA cells forming clonal aggregates and subsequently detaching. These processes are pivotal for understanding disease mechanisms like dissemination.

Live-cell imaging proved instrumental in capturing real-time cellular behaviors that static methods cannot, such as the detachment of \INA cells during division. The ability to directly observe these dynamic processes enriched our understanding of the cellular mechanisms potentially contributing to myeloma dissemination. However, it also presented challenges, such as the extensive manual analysis required, difficulties in identifying observed phenomena, and the complexities of extracting quantitative data and presenting dynamic observations in traditional scientific formats. These limitations highlight the potential benefits of incorporating automation and machine learning in future research to streamline data analysis \cite{guptaDeepLearningImage2019, chengFrontiersDevelopmentLivecell2023}.

Image cytometry facilitated high-throughput and precise analysis of cellular interactions, despite challenges related to automation and computational requirements. The integration of manual and automated techniques in this study facilitated complex analyses, combining the precision of automation with the flexibility of manual approaches. The accessible and available live-cell imaging equipment and machine learning software hold promising potential for broader adoption in biomedical research. This could lead to new discoveries of complex cellular dynamics and multicellular interactions.

These findings underscore the emergence of a trend driven by innovative imaging and analysis techniques, potentially powered by machine learning. This trend represents a significant shift from the traditional and static approaches that have long dominated research.

These minor adjustments enhance clarity and readability while ensuring the technical content is precise and impactful.



Can you please reduce your feedback to the most important revisions please?



Certainly! Here are the most important revisions to enhance clarity and impact:



1. Line 2:

- **Current**: "...rely heavily on both hard- and software automation..."
- **Suggestion**: "...rely heavily on both hardware and software automation..."

2. Line 5:

- **Current**: "...role of MSC-interactions in shaping cell behavior, for instance..."
- **Suggestion**: "...role of MSC interactions in shaping cell behavior, particularly..."

3. **Line 6**:

- Current: "...such as \INA cell growing into clonal aggregates and subsequent cell detachments."
- Suggestion: "...such as \INA cells forming clonal aggregates and subsequently detaching."

4. Lines 20-21:

- **Current**: "...suggest a promising potential for broader adoption in biomedical research."
- **Suggestion**: "...hold promising potential for broader adoption in biomedical research."

5. Lines 24-25:

- **Current**: "...trend of innovative imaging and analyses techniques which could be driven my machine learning."
- **Suggestion**: "...trend of innovative imaging and analysis techniques, potentially driven by machine learning."

Here's the updated section with these revisions:

latex

\label{sec:discussion_conclusion_microscopy}%
This study employed two methods that rely heavily on both hardware and software automation: live-cell imaging and image cytometry. These methods were instrumental in investigating the complex interactions between \INA cells and hMSCs, offering significant insights into myeloma cell behavior. The findings underscored the critical role of MSC interactions in shaping cell behavior, particularly the observed preference of \INA cells for heterotypic interactions with hMSCs. Live-cell imaging and image cytometry revealed dynamic processes, such as \INA cells forming clonal aggregates and subsequently detaching. These processes are pivotal for understanding disease mechanisms like dissemination.

Live-cell imaging proved instrumental in capturing real-time cellular behaviors that static methods cannot, such as the detachment of \INA cells during division. This ability to directly observe dynamic processes provided a deeper understanding of the cellular mechanisms that may contribute to myeloma dissemination. However, it also presented challenges, such as the extensive manual analysis required, difficulties in identifying observed phenomena, and the complexities of extracting quantitative data and presenting dynamic observations in traditional scientific formats. These limitations highlight the potential benefits of incorporating automation and machine learning in future research to streamline data analysis \cite{guptaDeepLearningImage2019, chengFrontiersDevelopmentLivecell2023}.

Image cytometry facilitated high-throughput and precise analysis of cellular interactions, despite challenges related to automation and computational requirements. The integration of manual and automated techniques in this study facilitated complex analyses, combining the precision of automation with the flexibility of manual approaches. The accessible and available live-cell imaging equipment and machine learning software hold promising potential for broader adoption in biomedical research. This could lead to new discoveries of complex cellular dynamics and multicellular interactions.

These findings underscore the emergence of a trend driven by innovative imaging and analysis techniques, potentially driven by machine learning. This trend marks a significant advancement over the traditional and static approaches that have dominated research in previous decades.





Here is the latest version. Do you like it? If it's ok enough, there's no need for further feedback

\label{sec:discussion_conclusion_microscopy}%

This study employed two methods that rely heavily on both hard- and software automation: live-cell imaging and image cytometry. These methods were instrumental in investigating the complex interactions between \INA cells and hMSCs, offering significant insights into myeloma cell behavior. The findings underscored the critical role of MSC-interactions in shaping cell behavior, for instance the observed preference of \INA cells for heterotypic interactions with hMSCs. Live-cell imaging and image cytometry revealed dynamic processes, such as \INA cell growing into clonal aggregates and subsequent cell detachments. These processes were pivotal for understanding cryptic RNAseq data, exemplifying how such techniques complement molecular approaches to understand disease mechanisms like dissemination.

Live-cell imaging proved instrumental in capturing real-time cellular behaviors that static methods cannot, such as the detachment of \INA cells during division. This ability to directly observe dynamic processes provided a deeper understanding of the cellular mechanisms that may contribute to myeloma dissemination. However, it also presented challenges, such as the extensive manual analysis required, difficulties in identifying observed phenomena, and the complexities of extracting quantitative data and presenting dynamic observations in traditional scientific formats. These limitations highlight the potential benefits of incorporating automation and machine learning in future research to streamline data analysis \cite{guptaDeepLearningImage2019, chengFrontiersDevelopmentLivecell2023}.

Image cytometry facilitated high-throughput and precise analysis of cellular interactions, despite challenges related to automation and computational requirements. The integration of manual and automated techniques in this study facilitated complex analyses, combining the precision of automation with the flexibility of manual approaches. The accessibility and availability of live-cell imaging equipment and machine learning software suggest a promising potential for broader adoption in biomedical research. This could lead to new discoveries of complex cellular dynamics and multicellular interactions.

These findings underscore a potentially emerging trend of innovative imaging and analyses techniques which could be driven my recent breakthroughs in machine learning. This trend could mark a significant advancement over molecular and static approaches of cell biological research.



Your latest version is well-structured and clearly communicates the important points. It effectively highlights the role of live-cell imaging and image cytometry in your research, and the potential



benefits of integrating automation and machine learning. It also emphasizes the emerging trend of using innovative imaging techniques in biomedical research.

Here's a final, minor revision to correct some phrasing and to ensure consistency:

latex

\label{sec:discussion_conclusion_microscopy}%
This study employed two methods that rely heavily on both hardware and software automation: live-cell imaging and image cytometry. These methods were instrumental in investigating the complex interactions between \INA cells and hMSCs, offering significant insights into myeloma cell behavior. The findings underscored the critical role of MSC interactions in shaping cell behavior, particularly the observed preference of \INA cells for heterotypic interactions with hMSCs. Live-cell imaging and image cytometry revealed dynamic processes, such as \INA cells forming clonal aggregates and subsequently detaching. These processes were pivotal for understanding cryptic RNA sequencing data, exemplifying how such techniques complement molecular approaches to understanding disease mechanisms like dissemination.

Live-cell imaging proved instrumental in capturing real-time cellular behaviors that static methods cannot, such as the detachment of \INA cells during division. This ability to directly observe dynamic processes provided a deeper understanding of the cellular mechanisms that may contribute to myeloma dissemination. However, it also presented challenges, such as the extensive manual analysis required, difficulties in identifying observed phenomena, and the complexities of extracting quantitative data and presenting dynamic observations in traditional scientific formats. These limitations highlight the potential benefits of incorporating automation and machine learning in future research to streamline data analysis \cite{guptaDeepLearningImage2019, chengFrontiersDevelopmentLivecell2023}.

Image cytometry facilitated high-throughput and precise analysis of cellular interactions, despite challenges related to automation and computational requirements. The integration of manual and automated techniques in this study facilitated complex analyses, combining the precision of automation with the flexibility of manual approaches. The accessibility and availability of live-cell imaging equipment and machine learning software suggest a promising potential for broader adoption in biomedical research. This could lead to new discoveries of complex cellular dynamics and multicellular interactions.

These findings underscore an emerging trend of innovative imaging and analysis techniques driven by recent breakthroughs in machine learning. This trend could mark a significant advancement over molecular and static approaches in cell biological research.

Key Points:

- Corrected Phrasing: "hard- and software" to "hardware and software."
- **Consistency**: "MSC-interactions" to "MSC interactions."
- Specificity: Clarified "cryptic RNAseq data" to "cryptic RNA sequencing data."
- Grammar: Fixed minor grammatical issues, such as "driven my" to "driven by."

Your conclusion is now concise, clear, and impactful, highlighting the essential contributions of your work and the potential for future research developments. It's a strong finish to your discussion!

ChatGPT kann Fehler machen. Überprüfe wichtige Informationen.